LIQUIDITY AND INTERNATIONAL BOND PRICING

by

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DECLARATION

"I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text"

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ABSTRACT

This thesis focuses on the liquidity risk and its impact on bond prices of the international markets and comprises three self-contained research papers.

In the first research paper, we examine the role of the liquidity in the pricing of sovereign U.S. dollar bonds in emerging markets. We extend Acharya and Pedersen's (2005) liquidity-adjusted capital asset pricing model to the bond market and find that both liquidity level and multiple liquidity risks are priced factors for the expected excess return of U.S. dollar bonds issued by developing countries. The combined effects of liquidity risk and liquidity level can explain as much as 1% per annum extra yield spread for the countries that have higher liquidity betas. Countries, which have a high correlation with the global market or U.S. stock market, have higher required bond returns than low correlation countries. The liquidity factor helps explain the credit spread puzzle of high yields. Our empirical results also support a flight to liquidity across the studied countries and are robust after controlling for bond characteristics and the U.S. risk factors.

The second research paper finds that both liquidity level and liquidity risk are important in explaining the cross-section of domestic government bond returns in 39 countries (both emerging and developed) around the world. After controlling for other market factors and bond characteristics, liquidity level and liquidity risk together can explain as much as 0.41% per annum of extra yield for the highest versus the lowest liquidity risk countries, which are China and Argentina respectively. There is also an evidence of liquidity spillovers from the U.S. equity market to domestic bond markets around the world. Employing a conditional model, which allows both time-series and cross-sectional variations in liquidity betas, we find that the impact of liquidity risk is time varying across two different regimes: it increases in times of high uncertainty and is always larger in emerging than in developed countries. Nevertheless, the price of risk or premium required by investors for holding this time-varying risk is relatively modest.

The third research paper examines whether liquidity spillovers between sovereign bonds are systematic or idiosyncratic in character. A theoretical model is developed, which demonstrates that idiosyncratic spillovers require returns to be correlated, whereas systematic spillovers require volatilities to be correlated. We apply the model to sovereign bonds in 35 emerging markets, aggregated for some analyses into Asian, European and Latin American regions. We find liquidity spillovers mainly from Latin America to the other regions and they are both systematic and idiosyncratic in character. Further cross-sectional analysis (by country) and time-series analysis (by region) show that systematic spillovers are more important than idiosyncratic spillovers. The conclusion is that most liquidity risk across emerging bond markets is systematic and therefore cannot easily be hedged away. This has important implications for portfolio selection by fund managers and for the regulation of systemic risk.

CHAPTER 1

INTRODUCTION AND OVERVIEW OF THE LITERATURE

This chapter contains both an introduction and overview of the literature in the following two sub-sessions.

1.1 Introduction

Academics have long agreed that less liquid securities should offer higher expected returns than would be justified by the market risk alone. Most previous studies of liquidity and asset pricing have focused on the price discount of illiquid securities (as compared with securities in a frictionless market) rather than on the risk premium that investors require for holding securities for which liquidity risks cannot be diversified away (i.e., for bearing systematic risk). In addition, the asset-pricing research, which includes liquidity as a factor, normally focuses on one particular market or one particular country, implicitly assuming that markets or countries can be separated in economic terms from another. Most empirical studies are concentrated on the U.S. stock market because of the availability of data. The assumption that liquidity risk is local and not global has been shown to be naive, following the recent global liquidity crisis over 2007-2009. The significance of liquidity for international asset pricing has not been systematically studied.

This PhD thesis, "*Liquidity and International Bond Pricing*", incorporates three self-contained research papers. We focus on bond markets because they provide a relatively good environment in which to test asset pricing models because the expected (forward-looking) return on bonds can be carefully constructed.[1] The first research paper is titled "*Liquidity Risk and the Pricing of Sovereign Bonds in Emerging Markets*".[2] An original question of how liquidity level and liquidity risk affect cross-sectional returns of emerging markets' sovereign bonds is investigated. No previous study has been made of the effects of liquidity (liquidity premium in particular, not only the illiquidity cost) on bond pricing on a global basis. We extend Acharya and Pedersen (2005)'s liquidity-adjusted capital asset pricing model to the international bond market. The main hypothesis is that there exists a market-wide liquidity shock, which is transmitted across countries (i.e., contagion in liquidity). If this contagion exists, securities for which returns and liquidity have a greater degree of co-movement with the market must also award investors higher expected returns. Empirical results show that both liquidity level and liquidity risk are priced factors for the expected returns of U.S. dollar bonds issued by developing countries (i.e., global or systematic liquidity risk is priced). Countries, which have a high correlation with the global market or U.S. stock market, have higher required bond returns than low correlation countries. Hence, the liquidity factor helps explain the credit spread puzzle of high yield on bonds. We also test whether the U.S. stock is a driving force in determining the average bond returns. However, evidence of a liquidity spillover from the U.S. stock market to emerging U.S. dollar bond market is statistically weak.

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[1] This contrasts with using stocks for which the historical (backward-looking) mean is often used as the proxy for the expected return.

[2] Sovereign bonds herein refer to U.S. dollar bonds issued by government entities.

So far, the study on the effect of liquidity on the cross-sectional asset pricing has been unconditional by nature. Although the first research paper finds that a bond's comovement with market factors is priced, the significance of both market and liquidity risks in explaining bond spreads seems to be time-varying. Further investigation on time-varying liquidity beta and liquidity risk premium can be beneficial. Therefore, the second research paper, *"Pricing of Government Bonds around the World and Time-varying Liquidity Risk"*, further investigate the effects of liquidity risk and time-varying risk on bond pricing around the world (both developed and emerging countries). We allow both time-series and cross-sectional variations in liquidity betas. Using a regime switching model, we find that the transition from the low to the high liquidity-beta state can be predicted by a decline in U.S. equity market performance (as a proxy for the world economy) and also by a rise in the global bond market volatility. The results suggest that the liquidity risk or liquidity beta is time varying across two different regimes: it increases in times of high uncertainty and is always larger in emerging than in developed countries. This is consistent with the results for U.S. equity markets: Watanabe and Watanabe (2008) report that the high-beta state for U.S. equities is associated with high equity volatility and preceded by a period of declining expectations about future market liquidity. Nevertheless, in the cross-sectional analyses, the price of risk or premium required by investors for holding this time-varying risk is relatively stable.

The first two research papers show the existence and importance of the commonality in liquidity (systematic or undiversified liquidity risk factor). Up to now, in most cases, liquidity is taken as an exogenous factor and its dynamic is disregarded. A well-specified dynamic liquidity risk may be a milestone in an accurate and more prefect asset pricing model. To this regard, the third research paper, titled *"Liquidity Spillovers: Theory and Evidence from Emerging Bond Markets"*, aims to study how and why liquidity is transmitted across markets in the international setting. This paper will examine the dynamic interaction of liquidity across national boundaries, i.e., how does liquidity transmit from a certain market to the others and how important are systematic and idiosyncratic liquidity in explaining the liquidity spillovers. Our model suggests different commonalities caused by systematic and idiosyncratic liquidity shocks. Idiosyncratic shocks induce spillovers in liquidity only if asset returns are correlated. Systematic liquidity shocks are associated with spillovers in volatility. Our empirical results find the consistent patterns of liquidity spillovers across regions from Asia to Europe and from Latin America to both Asia and Europe. And they show that systematic and idiosyncratic liquidity shocks are both relevant in explaining liquidity transmission across regions. However, further empirical investigation suggests that the commonality in liquidity is more associated with that in volatility than that in returns. In other words, the liquidity risk or the co-movement of liquidity with the market factor is likely a result of systematic liquidity shocks rather than idiosyncratic ones. Moreover, we find that the commonality in liquidity varies significantly over time and sharply increases during global financial crises. In line with the results found in the second research paper, these confirm that liquidity risk is time-varying.

1.2 Overview of Related Literature

In order to avoid repetition, this section provides an overview rather than a complete list of related literature on liquidity and bond pricing. The specific literature will be covered in each associated research paper. The following two sub-sections briefly discuss how previous studies measure liquidity and how liquidity has been related in those studies to bond spreads.

1.2.1 Liquidity measures

Liquidity (or its converse, illiquidity) is hard to measure precisely as liquidity is a relative measure. A market is more liquid than another if it is possible: (i) at a given price, to buy or sell more rapidly a given quantity of an asset (e.g., in one minute rather than ten); or (ii) at the same speed and price, to buy or sell more of the asset (e.g. $100 million of asset rather than $1 million). In other words, liquidity relates to the speed with which an asset can be traded and the price impact for the purchase or sale of a given quantity. As far as the current theories are concerned, the potential sources of illiquidity are:

(i) Transaction costs such as exchange fees, brokerage fees, order-processing costs or taxes. This source of illiquidity is most obvious and least interesting because these costs should be fairly constant in the short-run and so are unlikely to determine short-term changes in liquidity.

(ii) Inventory risk faced by market makers, e.g., Stoll (1978) and Amihud and Mendelson (1980). This risk arises mainly from unexpected variation in both order flows and future prices, leading to risks in the size of the inventory that dealers need to keep on-hand. The bid/ask spread needs to compensate dealers for holding less than fully diversified portfolios.

(iii) Information asymmetries, e.g., Bagehot (1971), Glosten and Milgrom (1985) and Easley, Hvidkjaer and O'Hara (2002).[3] Adverse selection problems arise when a group of investors– known in the literature as the "informed" traders– have private information on the value of an asset not currently reflected in prices. Informed traders will want to trade only if the current ask price they face is below– or the bid price is above– the fundamental value of the asset. Since the uniformed market participants (particularly, dealers) will always make a loss from dealing with informed traders, they have to recoup these losses from other investors by charging a larger bid/ask spread for trading.

(iv) Market impact costs, e.g., Kyle (1985).[4] These costs reflect the price concession incurred by a buyer or a seller when trading, i.e., a premium when buying or a discount when selling. For small trades, the market impact is confined to the bid/ask spread, which is the difference between the buying and selling price quoted by liquidity providers.

(v) Search frictions and delay costs, e.g., Longstaff (1995) and Duffie, Garleanu and Pedersen (2005), which are incurred when a trader looks for better prices than those quoted in the market or wishes to minimize the price impact cost (component (iv)) of her order. To minimize the price impact, the trader bears

[3] The model of Easley at el. (2002) implies that a bid/ask spread is greater if the probability of trading with informed traders is larger.

[4] Kyle (1985) describes the market impact as the price change per unit of net order flow. The less liquid stock has a larger impact.

search and delay costs resulting from the fact that the trade is not executed immediately and the market can turn against her

Note that some of liquidity components are correlated and overlap, for example, an asset with a high bid/ask spread or high price impact often has high transaction costs as well as friction and delay costs.

With respect to measuring liquidity, the obvious measure is the bid/ask spread. Of course, the bid/ask spread is quoted for a given quantity of asset and it might be quite different for a larger quantity. There can therefore be an "illusion" of liquidity. Often studies have to resort to other measures because they do not have reliable bid/ask data. And with the multi-dimensional nature of liquidity, it is not surprising that the literature on market microstructure and liquidity proposes many different measures or proxies.

While the most appropriate liquidity measure is still debatable[5], a widely used choice in literature is a price impact measure developed by Amihud (2002), which is denoted as ILLIQ (an absolute change in return per dollar volume). However, most corporate bonds and sovereign bonds have no daily volume data. Another approach by Amihud and Mendelsen (1987) provides a framework based on the idea that the intrinsic value of a firm may differ from its market value because of a liquidity premium. Lesmond, Ogden and Trzcinka (1999) outline an estimation procedure for this called the LOT measure. The LOT measure is similar to one based on zero returns, but extracts more information including the spread and other costs that may impinge on informed trade such as

[5] While trading volume is an intuitive and traditional measure of market liquidity, main drawback is that it is also associated with price volatility, which tends to be negatively related to market liquidity. This becomes more apparent during periods of stress. In addition, both trading volume and turnover do not directly capture the buying and selling costs over the long time.

commission cost, opportunity cost and price impact cost. If the value of the information is less than the transaction cost of implementing a trade, the market participants will choose not to trade and zero returns are observed. The advantage of this measure is that it requires only a time series of daily returns. Bekaert, Harvey and Lundblad (2007) show that this measure is highly correlated with more traditional measures of transactions cost for emerging equity markets. This measure also receives support from Lesmond (2005) in his study of emerging equity markets. Using more than 4,000 U.S. corporate bonds, Chen, Lesmond and Wei (2007) examine several measures of bond-specific liquidity, i.e., traditional bid/ask spread, percentage of zero return and LOT. They report that percentage of zeros and LOT are highly associated with the underlying bid/ask spread and in contrast to Longstaff, Mithal and Neis (2005), the paper finds little evidence of the size of issue in explaining bond liquidity.

A very recent measure of liquidity is “latent liquidity”, which is the weighted average turnover of funds holding a particular bond. The weights are the funds’ fractional holdings of the bond. Latent liquidity reflects the degree to which a bond is held by those investors who are expected to trade more frequently. While it can be used to measure liquidity in markets with sparse transactions data, its calculation requires that the holding and turnover data of a security are available (from the custodian houses). Using this measure, Chacko (2006) and Mahanti, Nashikkar, Subrahmanyam, Chacko and Mallik (2008) show that liquidity is priced in the U.S. corporate bond market.

Because of the data availability, we are fortunate to be able to employ the bid/ask spread as a direct measure of liquidity throughout this thesis. The bid/ask spread reflects some part of all liquidity components (i) to (v). Therefore, it is not surprising that many studies including Fleming (2003) and D’Souza, Gaa and Yang (2003) support bid/ask spread as one of the most appropriate liquidity indicators due to its high degree of correlation with other measures such as price impact, benchmark/non-benchmark yield spreads and price volatility. In addition, it remains the most commonly used benchmark for liquidity measure.

1.2.2 Liquidity and bond prices

There are two approaches to modeling prices for risky bonds– the structural and reduced-form models– and neither incorporates the effect of liquidity or liquidity risk.

The early work in the structural model, for example, Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995), Anderson and Sundaresan (1996) and Mella-Barral and Perraudin (1997), ignores the liquidity effect on the bond spread. The empirical work by Eom, Helwege and Huang (2004) shows that structural models do not generate spreads as high as those seen in the bond market. Liquidity risk might help to alleviate this problem because riskier bonds usually have more liquidity constraints. In addition, the structural models, which directly capture the default incentives and solvency of the issuer, can be problematic when we model sovereign bonds, which are the focus of this thesis. As in Duffie, Pedersen and Singleton (2003), the incentive to sovereign default is rather complex. A holder of sovereign debt may not have recourse to a bankruptcy code in the event of default. Sovereign default is largely a political decision. Governments trade off the cost of making debt payments against reputation costs (Eaton and Gersovitz (1981)). When it defaults, a country may lose assets held abroad, but assets held within the country cannot be seized as collateral. For sovereign debt, willingness to pay is more important than ability to pay. Note, however, that the incentive of a corporation to default is much simpler.

Another approach to bond spread modeling is the reduced-form (or hazard rate) model. This model does not try to explain why default happens, rather it models default explicitly by an intensity process. But even in the reduced-form models such as Duffie and Singleton (1999) and Jarrow, Lando, and Turnbull (1997), the dynamics of bond values are specified in a way that is appropriate for fitting the evolution of credit quality rather than liquidity. The reduced-form models again cannot fully explain bond spread with the default risk and recovery rate alone. While the best way of incorporating a liquidity premium into a theoretical pricing model remains a subject for research, a recent paper by Ericsson and Renault (2006) has begun to examine this issue.

For empirical works, among others, Elton, Gruber, Agrawal and Mann (2001) and Huang and Huang (2003) confirm that corporate bond yields are too high to be explained by default alone. Many papers find that taxes, a market-risk premium and jump-risk premium can explain some portion of bond yield spreads, but not the full magnitude (tax effects: Elton et al. (2001), Amato and Remolona (2003) and Liu, Shi, Wang and Wu (2007) and jump risk premium: Amato and Remolona (2003), Driessen (2005), Cremers, Driessen and Maenhout (2008) and Collin-Dufresne, Goldstein and Helwege (2010)). Many studies argue that there must be a common factor other than credit risk behind the change in the credit spread in the corporate bond and sovereign bond markets (for example, Collin-Dufresne, Goldstein and Marting (2001) and Weigel and Gemmill (2006)) and the country-specific fundamentals alone cannot explain the change in the international sovereign bond spread (for example, Cantor and Packer (1996), Eichengreen and Mody (1998) and Kamin and von Kleist (1999)). Using the data from CDS spreads, Longstaff, Pan, Pedersen and Singleton (2007) find that returns from sovereign credit are mainly attributed to global risk with only a small country-specific credit risk premium. One of the possible candidates for that missing factor may be liquidity, both liquidity level and liquidity risk. If a liquidity risk premium is an important feature of these data, the focus on emerging markets should yield powerful tests and useful independent evidence because liquidity is particularly important in these markets.

Therefore, the focus of this thesis, *"Liquidity and International Bond Pricing"*, is liquidity and its impact on bond prices in the international markets. In doing so, the next three chapters incorporate three self-contained research papers. Chapter 2 is the first research paper, "*Liquidity Risk and the Pricing of Sovereign Bonds in Emerging Markets".* It originally deals with multiple liquidity-risk channels for the U.S. dollar emerging bond markets. Chapter 3 presents the second research paper, *"Pricing of Government Bonds around the World and Time-varying Liquidity Risk"*, which is the first study of the effects of liquidity risk and its time-variation on local-currency government bond prices in a comprehensive set of both developed and emerging countries. The last research paper, *"Liquidity Spillovers: Theory and Evidence from Emerging Bond Markets"*, in Chapter 4 takes a step back and investigates the reason behind the existence of liquidity risk (i.e., contagion in liquidity or liquidity spillover across markets) in the international bond market settings. Chapter 5 provides the thesis's concluding remarks.

CHAPTER 2

LIQUIDITY RISK AND THE PRICING OF SOVEREIGN BONDS IN EMERGING MARKETS

Abstract

This paper examines the role of the liquidity in the pricing of sovereign U.S. dollar bonds in emerging markets. We extend Acharya and Pedersen's (2005) liquidity-adjusted capital asset pricing model to the bond market and find that both liquidity level and multiple liquidity risks are priced factors for the expected excess return of U.S. dollar bonds issued by developing countries. The combined effects of liquidity risk and liquidity level can explain as much as 1% per annum extra yield spread for the countries that have higher liquidity betas. Countries, which have a high correlation with the global market or U.S. stock market, have higher required bond returns than low correlation countries. The liquidity factor helps explain the credit spread puzzle of high yields. Our empirical results also support a flight to liquidity across the studied countries and are robust after controlling for bond characteristics and the U.S. risk factors.

2.1 Introduction

One of the main economic questions in finance is why average returns vary across assets. Investors, who hold assets that have greater systematic risk exposure or higher betas, should be compensated by higher expected returns. However, the non-default components of yield spreads cannot be explained by a single market risk premium alone.[6] Recent literature has given more attention to liquidity risk (see more discussion in the Related Literature section below). Many studies argue that investors require higher expected returns or liquidity premia in order to compensate for holding less liquid securities. Possibly due to the paucity of information on bond markets, heretofore most previous studies of liquidity have concentrated on stock markets, despite the fact that bonds are generally considered to be less liquid securities.

There is widespread evidence that liquidity (both in terms of a security's individual characteristics and its systematic risk) is priced in the security market. Acharya and Pedersen (2005) develop a unified equilibrium model including both liquidity level and liquidity risk, called the liquidity-adjusted capital asset pricing model (henceforth denoted as "LCAPM"). In addition to expected illiquidity cost and the traditional capital asset pricing model (henceforth denoted as "CAPM") market beta, this new model captures three possible different forms of liquidity risk for an asset: (i) commonality in liquidity with the market liquidity, $\mathrm{Cov}(c^i,c^M)$, (ii) return sensitivity to market liquidity, $\mathrm{Cov}(r^i,c^M)$ and (iii) liquidity sensitivity to market returns, $\mathrm{Cov}(c^i,r^M)$, where r and c are the return and illiquidity cost. Superscripts i and M represent the asset i and aggregate market respectively. They apply the model to the U.S. stock market.

[6] Work by Elton, Gruber, Agrawal and Mann (2001) argues that non-default component consists of risk premium and tax effects.

Following Acharya and Pedersen (2005), this paper extends the application of the LCAPM to the international bond markets from the perspective of an U.S. investor. Moreover, the bond-version LCAMP is modified and jointly tested against the U.S. stock market. We use the bonds in the JPMorgan Emerging Markets Bond Index (EMBI), which has comprehensive coverage of U.S. dollar emerging market bonds issued by sovereign and quasi-sovereign entities.[7]

As mentioned, studies on liquidity and asset pricing have been concentrated on the highly-liquid U.S. stock market because of data availability. Consequently, the question of whether liquidity is priced in many studies does not have a consensus answer. Despite their relative lack of market data, bond markets can provide some advantages in testing the liquidity channel in asset pricing as follows:

1. Unlike stock returns, the ex ante risk premium for bond returns is readily available. The bond yield (forward-looking internal rate of return), after adjusting for the expected loss, provides a more accurate and cleaner measure of the expected returns than does a simple average of realized past returns as used for stock market. Subsequently, this leads to more reliable empirical asset pricing tests for bonds. The construction of the expected bond returns in this paper follows the work by Campello, Chen and Zhang (2008).
2. Bonds, in general, have significantly lower liquidity compared with stocks. Therefore, they provide an ideal setting in which to examine liquidity effects on expected returns. Several papers on stocks, for example, Amihud (2002) and Chordia, Roll and Subrahmanyam (2000), focus on equally-weighted returns and

[7] From the perspective of an U.S. investor, EMBI bonds have no foreign exchange risk.

illiquidity measures as a way to compensate for the over-representation in their samples of highly liquid U.S. stocks. With bonds, such adjustment is less needed. In addition, since the U.S. equity markets contain a huge number of highly diversified investors, the liquidity effects in emerging bond markets may be stronger than those in the U.S. equity markets.

3. There are very few papers that study the effects of both liquidity <u>level</u> and liquidity <u>risk</u> on expected bond returns. This paper offers a liquidity explanation for unexplained credit spreads or "the credit spread puzzle".

Our results show the effects of three liquidity <u>risk</u> measures on expected excess bond returns for the countries, which have higher liquidity beta, to be as follows: (i) the risk premium resulting from the co-movement between country-specific liquidity and market liquidity, Cov(c^i,c^M), is small, being 0.03% per annum; (ii) the risk premium due to the return sensitivity to market liquidity, Cov(r^i,c^M), is 0.11% per annum; (iii) the risk premium owing to the commonality in the country-specific liquidity and market returns, Cov(c^i,r^M), is 0.70% per annum. Base on historical average turnover, the return premium due to the expected <u>level</u> of liquidity is estimated to be 0.16% annually. Therefore, the total effect of the liquidity risk and liquidity level can be as much as 1.00% per annum (100 basis points) between the highest liquidity beta countries and the lowest (or about 35% of the 290 basis points difference in spreads between Croatia and Ghana). The empirical findings also indicate that there is a flight to liquidity across all emerging countries during our study period. Our results are still robust even if we control the bond's characteristics and the U.S. risk factors.

The paper is organized as follows. Section 2.2 describes the related literature on liquidity and asset pricing. Section 2.3 includes the explanation of data used, the construction of liquidity measures and the brief introduction to the LCAPM. The detailed methodology is presented in Section 2.4. Empirical results are reported in Section 2.5. Section 2.6 provides the robustness tests. And finally Section 2.7 concludes.

2.2 Related Literature

There have been many papers that relate an individual security's liquidity to its price. Amihud and Mendelson (1986 and 1989) study the effect of liquidity on expected stock returns and find that they are an increasing and concave function of illiquidity costs as measured by the stock's bid/ask spread. Using a finer measure of illiquidity (in response to unexpected trading), Brennan and Subrahmanyam (1996) find that liquidity has a positive and significant effect on required returns after adjusting for the Fama and French factors and after allowing for the effects of the stock price level. Datar, Naik and Radcliffe (1998) find a strong negative relation between average stock returns and turnover as a measure of liquidity.[8] Consistent with other studies, Amihud (2002)'s ILLIQ measure of illiquidity has a positive effect on ex ante expected stock returns in the cross-section of NYSE stocks from 1963–1996, controlling for the impacts of beta, size, volatility, dividend yield and past returns.[9] Interestingly, Chordia, Subrahmanyam and Anshuman (2001) extend the work by Brennan, Chordia and Subrahmanyam (1998) by including the stock characteristics and the volatility of trading activity. Their results indicate that both level and volatility of trading activity have a negative and significant effect on cross-sectional risk-adjusted returns. The authors suggest that the effect of the second moment of liquidity may result from its correlation with some omitted and unknown risk factor.

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[8] The turnover or the reciprocal of hold period is defined as the ratio of the security's trading volume to the amount outstanding.

[9] The ILLIQ measure is defined as the absolute change in return per dollar volume. A security with the higher ILLIQ measure has lower liquidity.

Until recently, when Chordia, Roll and Subrahmanyam (2000), Hasbrouck and Seppi (2001) and Huberman and Halka (2001) found commonality in the individual security's liquidity and market-wide liquidity, people considered liquidity to be a diversified risk factor. Pastor and Stambaugh (2003) are the first to investigate the liquidity risk and show that U.S. stock returns are exposed to market-wide liquidity. Stocks with greater systematic liquidity risk (i.e., their returns are highly correlated with the market liquidity) are compensated by higher returns. They also report that the average returns on stocks with high sensitivity exceed those for stocks with low sensitivity by 7.5% per annum. Similar results are presented by Martinez, Nieto, Rubio and Tapia (2005) using Spanish stock market data from 1993–2000.

Combining empirical findings that return sensitivity to market liquidity is priced and that liquidity co-moves with returns and predicts future returns, Acharya and Pedersen (2005) develop an asset pricing model that includes both liquidity <u>level</u> and liquidity <u>risk</u>. Expected excess return over the risk-free rate is a function of both the expected illiquidity cost and four systematic risk variables: the market return beta, $\beta^1 = \text{Cov}(r^i,r^M)/\text{Var}(r^M - c^M)$ and another three liquidity betas, $\beta^2 = \text{Cov}(c^i,c^M)/\text{Var}(r^M - c^M)$, $\beta^3 = \text{Cov}(r^i,c^M)/\text{Var}(r^M - c^M)$ and $\beta^4 = \text{Cov}(c^i,r^M)/\text{Var}(r^M - c^M)$, where r^i is the gross return of security ***i***. c^i and c^M are the illiquidity cost of individual stock *i* and the market respectively. $r^M - c^M$ is the market net return after paying illiquidity cost. In their cross-sectional analysis, liquidity risk explains about 1.1% of returns, whereas the premium for liquidity level is 3.5%. The liquidity risk in previous studies is nested in the LCAPM of Acharya and Pedersen (2005). For example, the liquidity risk in Pastor and Stambaugh (2003) (i.e., return sensitivity to market liquidity, β^3) is one of the three covariance components of liquidity risk in the Acharya and Pedersen (2005)'s model.

Surprisingly, empirical work on the effects of liquidity on asset pricing usually employ data from U.S. stock markets, for which the liquidity effects are substantially mitigated because of client effects in portfolio choice. Works outside U.S. are rare. Rouwenhorst (1999) reports a strong cross-sectional correlation between the return factors and stock turnover in 20 emerging countries. Using stock data from Japan, U.K. and U.S. from 1980 to 2001, Stahel (2005) finds that global liquidity is priced. Bekaert, Harvey and Lundblad (2007) find that models incorporating local liquidity risks for stock markets outperform all other models that use only market-risk factors in predicting future returns. Interestingly, their results show that while the price of local market risk is not significant, the price of local as well as global liquidity risks is positive and significant. Jun, Marathe and Shawky (2003) find that the stock returns in emerging countries are positively correlated with aggregate market liquidity as measured by turnover ratio, trading value and turnover. The results hold in both cross-section and time series. Liang and Wei (2006) employ data from 23 developed countries' stock markets and find that global liquidity risk in addition to the Fama-French three factors is positively priced in the cross-sectional return analysis. Work by Lee (2010) also finds similar results with individual stocks, but he includes 48 developed and emerging countries around the world. All of these previous works on international asset pricing and liquidity utilize stock market data and not bonds.

In terms of pricing, liquidity may help to explain the credit spread puzzle in the bond market, where spreads on bonds tend to be a lot higher than would be implied by expected default losses alone. Many papers find that tax, a market-risk premium and a jump-risk premium can explain some portion of bond yield spreads, but not the full magnitude (tax effect: Elton, Gruber, Agrawal and Mann (2001), Amato and Remolona

(2003) and Liu, Shi, Wang and Wu (2007) and jump risk premium: Amato and Remolona (2003), Driessen (2005), Cremers, Driessen and Maenhout (2008) and Collin-Dufresne, Goldstein and Helwege (2010)). Theoretical bond pricing models, whether structural models or reduced-form models, usually ignore liquidity effects and produce spreads that are smaller than observed ones (see Eom, Helwege and Huang (2004)).[10] Even in the reduced-form models such as Duffie and Singleton (1999) and Jarrow, Lando and Turnbull (1997), the dynamics of bond values are specified in a way that is appropriate for fitting the evolution of credit quality rather than liquidity. While the best way of incorporating a liquidity premium into a theoretical pricing model remains a subject for research, a recent paper by Ericsson and Renault (2006) has begun to examine this question.

Many empirical works support that liquidity level is priced in U.S. corporate bonds (e.g., Perraudin and Taylor (2003), Houweling, Mentink and Vorst (2005), Chacko (2006) and Chen, Lesmond and Wei (2007)). For example, in a study of over 4,000 U.S. corporate bonds, Chen et al. (2007) find empirical evidence that liquidity is a key determinant in yield spreads both in terms of yield levels and yield changes over time. Cossin and Lu (2005), Longstaff, Mithal and Neis (2005) and Chen, Cheng and Wu (2005) use information from credit default swaps (CDS) to relate the credit spreads that cannot be explained by the default component to bond-specific liquidity. However, only two papers, by De Jong and Driessen (2006) and Jacoby, Theocharides and Zheng (2007), have thus far investigated the pricing of liquidity risk (systemic change in

[10] See for example of structural models, Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995), Anderson and Sundaresan (1996) and Mella-Barral and Perraudin (1997). By contrast, the reduce form models does not try to explain why default happens, rather they model default explicitly by intensity process.

liquidity) per se in the bond market. De Jong and Driessen (2005) employ a two-step multifactor model that includes two market risk factors: the U.S. stock market index return and the change in the market volatility (using the VIX index) and two liquidity risk factors: the Amihud (2002) ILLIQ measure for stock market (a proxy for the stock market illiquidity) and the quoted bid/ask spread for long maturity U.S. Treasury bond (a proxy for the bond market illiquidity). In their first step, the factor loading and the liquidity betas of the bond portfolio are estimated from the time-series regression.[11] They find that bonds with lower credit ratings and longer maturities have higher exposure to both liquidity and stock index factors. In the second step, a cross-sectional regression of the expected bond returns on the two liquidity betas shows that liquidity risk is priced. The liquidity premia for the long-term investment grade and speculative bonds are around 0.6% and 1.5% per annum respectively. Jacoby et al. (2007) follow the LCAPM framework and find similar results that liquidity risk monotonically increases with illiquidity for U.S. corporate bonds and the liquidity risk is priced in cross-sectional analysis. However, their sample period only covers July 2002 to December 2004 because they extract the corporate bond transaction data (including the transaction dates, prices and quantities traded) from the recently-established TRACE system, which allows them to compute a measure of illiquidity similar to ILLIQ.[12]

While there are a relatively large number of studies about U.S. market or international stock market liquidity, no paper extends the impact of liquidity risk on expected returns

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[11] Liquidity beta in their paper is comparable to the one in Pastor and Stambaugh (2003) and β^3 in Acharya and Pedersen (2005).

[12] TRACE system is introduced by the National Association of Securities Dealers (NASD) in 2002 to make the corporate bond market more transparent. The dealers are obliged to report the over-the-counter secondary market transactions. The current reporting time is 15 minutes.

to the international bond markets especially to emerging bond markets for which illiquidity is a major concern. Domowitz, Glen and Madhavan (2001) report that transaction cost in emerging markets is significantly higher than that in developed markets, even after correcting for factors such as market capitalization and volatility. Hund and Lesmond (2008), who apply a similar methodology to Chen et al. (2007), investigate 16 emerging bond markets during 1997-2004 and find that illiquidity cost is significant in explaining the cross-sectional yield level and variation in yields of sovereign and corporate bonds. Beber, Brandt and Kavajecz (2009) and Favero, Pagano and von Thadden (2010) find that liquidity is an important factor in explaining European sovereign bond spreads after the introduction of the Euro. Many studies question whether there is a common factor other than credit risk behind the change in the credit spread in the corporate bond and sovereign bond markets (for example, Collin-Dufresne, Goldstein and Marting (2001) and Diaz-Weigel and Gemmill (2006)) and the country-specific fundamentals alone cannot explain the change in the sovereign bond spread (for example, Kamin and von Kleist (1999), Eichengreen and Mody (1998) and Cantor and Packer (1996)). Using the data from CDS spreads, Longstaff, Pan, Pedersen and Singleton (2007) find that returns from sovereign credit are mainly attributed to global risk with only a small country-specific credit risk premium. Global liquidity risk is perhaps our missing answer.

Our study is original in that it extends the LCAPM to jointly investigate how liquidity level and liquidity risk have an impact on the cross-sectional returns of international bond markets. A main hypothesis is that there exist shocks to market-wide liquidity, which are transmitted across countries (i.e., contagion or spillover in liquidity). In the main specification, we group the sovereign bonds according to the country of issuance.

This is to avoid the size effects occurring when the existing literature usually sorts the test portfolio by size.[13] With a country-specific portfolio, contagion effects of market-wide liquidity in emerging countries can be examined. We also modify the LCAPM model to include the U.S. stock risk factors and we confirm the empirical findings of the previous studies that U.S. equity markets play a significant role in the expected bond returns in emerging markets.

[13] The study by Lewellen, Nagel and Shanken (2010) suggests that since there is the strong factor structure of size-B/M portfolios, any factor is likely to produce betas that line up with expected returns. One simple solution is to expand the set of test assets to include other portfolios, sorted by industry, beta, or other characteristics, not by any criteria related to the size and B/M.

2.3 Data and the Liquidity-adjusted Capital Asset Pricing Model (LCAPM)

2.3.1 Data and summary statistics

After the First World War, financial intermediation in developing countries was limited almost entirely to the loan market (Mauro, Sussman and Yafeh (2006)). There was no significant activity in the international bond markets before the introduction of Brady bonds in the early 1990s as the repackage of the non-performing loans. Mauro et al. (2006) p.19 report the change in the composition of sovereign debt from bank loans to bonds in the emerging market countries. They also present the rapid growth of international bonds issued by emerging market countries from almost nothing in early 1990s to more than 300 billion U.S. dollar in 2001. Unlike the bond structure before the First World War, most of the sovereign bonds now have 5 to 10 year maturity rather than having maturity of 20 years or more.

In response to such expansion, J.P. Morgan established a new database on 31 December 1993. Their MorganMarket system reports on a daily basis the Emerging Market Bond Index (EMBI), which is the most comprehensive U.S. dollar emerging-markets debt benchmark. Included in the EMBI are U.S. dollar-denominated Brady bonds, Eurobonds and traded loans issued by sovereign and quasi-sovereign entities.[14] The

[14] The EMBI defines emerging markets countries with a combination of World-Bank defined per capita income brackets and each country's debt-restructuring history. These two criteria allow the EMBI to include a number of higher-rated countries that international investors have, nevertheless, considered part of the emerging markets universe.

following 42 countries are (or used to be) included in the EMBI and are used in this study.[15]

Latin America	Asia	Europe	Africa
1. Argentina (AR)	1. China (CN)	1. Bulgaria (BG)	1. Egypt (EG)
2. Brazil (BR)	2. Indonesia (ID)	2. Serbia (CS)	2. Gabon (GA)
3. Belize (BZ)	3. Korea (KR)	3. Greece (GR)	3. Ghana (GH)
4. Chile (CL)	4. Kazakhstan (KZ)	4. Croatia (HR)	4. Morocco (MA)
5. Columbia (CO)	5. Lebanon (LB)	5. Hungary (HU)	5. Nigeria (NG)
6. Dominican (DO)	6. Sri Lanka (LK)	6. Poland (PL)	6. Tunisia (TN)
7. Ecuador (EC)	7. Malaysia (MY)	7. Russia (RU)	7. South Africa (ZA)
8. Jamaica (JM)	8. Philippines (PH)	8. Turkey (TR)	
9. Mexico (MX)	9. Pakistan (PK)	9. Ukraine (UA)	
10. Panama (PA)	10. Thailand (TH)		
11. Peru (PE)	11. Vietnam (VN)		
12. El Salvador (SV)			
13. Trinidad Tobago (TT)			
14. Uruguay (UY)			
15. Venezuela (VE)			

From the universe of emerging-market countries, the eligible bonds in the EMBI consist of those that are:[16]

- denominated in U.S. dollar with face amount outstanding of 50 million U.S. dollar or more
- issued by sovereign or quasi-sovereign entities[17]
- at least 2.5 years away from maturity at the inclusion (a bond is removed from the EMBI when its maturity is less than 12 months)

[15] As of 1 January 2008 the MSCI Emerging Markets Equity Index consisted of the following 25 emerging market country indices: Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Israel, Jordan, Korea, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey. Most of them are included in the EMBI.

[16] More detail about how to construct the EMBI can be found in the Introducing the J.P. Morgan Emerging Markets Bond Index Global (EMBI Global), 3 August 1999.

[17] Quasi-sovereign is defined as an entity that is 100% guaranteed or 100% owned by the national government. Therefore, its credit rating is equivalent to the sovereign credit rating. However, more than 90% of the market value is the bonds issued by sovereign.

- accessible to international investors (a country is excluded if it introduces capital controls or tax hurdles to international investors)
- issued with legal jurisdiction that is domestic to a G7 country
- able to settle internationally either through Euroclear or another institution domiciled outside the issuing country
- available for the bid and offer prices on a daily basis either from an interdealer broker or JP Morgan[18]

The above criteria ensure that international investors consider such bonds as a part of the emerging-market portfolio, which to some certain extent implies that the risk in different countries commands the same influence on expected returns. The sample period in this study spans from 5 January 1995 to 8 August 2008. To ensure the maximum number of data points, we employ weekly data.[19] With approximately 200 eligible bonds, the market value of EMBI is about 295 billion U.S. dollar on 8 August 2008, rising more than threefold since 1995. Ever since started, Latin American countries have accounted for the largest proportion of the total market capitalization, although their proportion is decreasing gradually. More than half of the bonds are of investment grade. As of June 2008, the EMBI includes about 60% of total international debt securities issued in foreign currency by developing countries.[20] Thus, our data set

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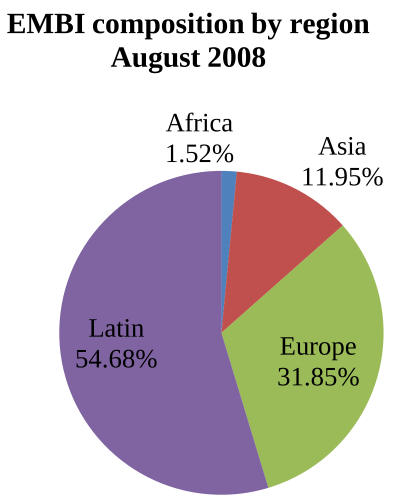
[18] By contrast, the bid/ask spreads that are obtained from Bloomberg by construction tend to under-estimate the illiquidity as they are computed from the highest offer yields and lowest bid yields quoted by several bond dealers .

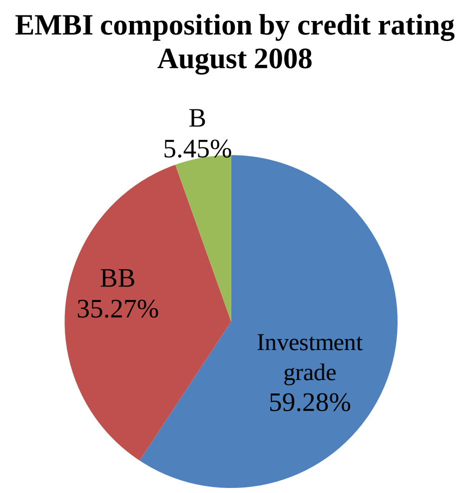
[19] The weekly interval was chosen as opposed to daily or monthly as a compromise between the problems of measurement errors inherent in daily data and sampling inefficiencies associated with longer intervals.

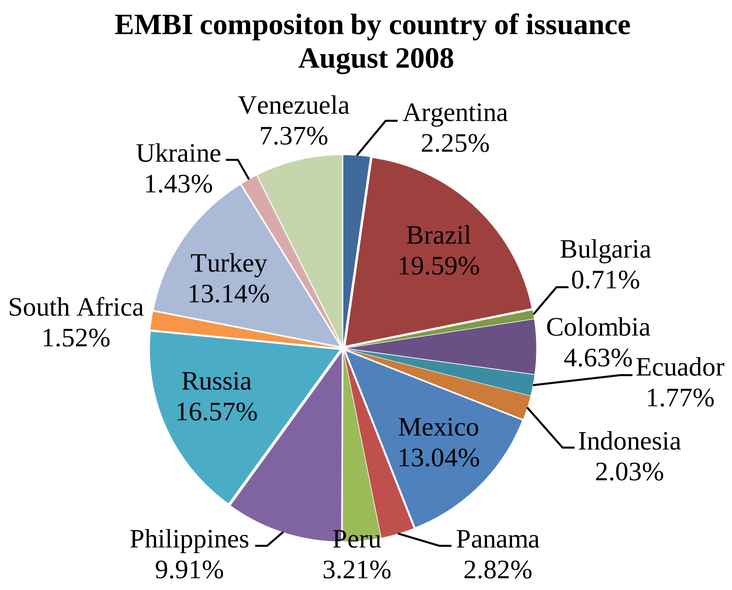
[20] The international debt securities, including money market instruments, notes, and bonds, issued by the interested countries, have the amount outstanding of 480 billion U.S. dollar as of June 2008 (source: the Bank for International Settlement Quarterly Review, September 2008).

may be considered representative for the universe of debt securities in the emerging countries. The composition of the EMBI market capitalization by region, credit rating and country of issuance is reported in Figure 2-1.

Figure 2-1: Emerging Market Bond Index (EMBI) composition by region, credit rating and country of issuance as of August 2008







In additional to the total market capitalization, MorganMarket provides daily information on the bid/ask spreads, bond yields, yield spreads over U.S. Treasury with the same maturity, coupons, maturities and modified durations for each individual bond in the EMBI. Table 2-1 summarizes the statistics of data used in the paper. While bond characteristics, such as bond maturity and coupon, have been quite stable over our sample period, yield spreads over U.S. treasuries at the corresponding maturity and percentage quoted bid/ask spreads have been quite volatile especially during the Russian default, the LTCM crisis and the Brazilian Real devaluation in 1998 and 1999. This suggests that it may be difficult to discern any difference in spreads, which are due to bond characteristics because returns are dominated by a number of "one-off" events.

Table 2-1: Summary statistics on Emerging Market Bond Index (EMBI)
This table reports the year-by-year summary statistics on all eligible U.S. dollar sovereign bonds included in EMBI. The weekly-data sample spans from January 1998 to August 2008. The data start from 1998 because some data do not available for the years 1995 to 1997. The mean (except for total return) are reported year-by-year. The numbers in the parentheses is standard deviation. Yield spread over U.S. Treasury is defined as the EMBI yield minus the U.S. Treasury yield at the corresponding maturity. Percentage quoted bid/ask spread is calculated as, (quoted ask price$_t^{EMBI}$ – quoted bid price$_t^{EMBI}$)/ mid price$_t^{EMBI}$, which reflects illiquidity cost of the overall international bond markets. Total return is the EMBI realized return taking account of capital gain, coupon and accrued interest. Bond maturity, modified duration and coupon are the market-weighted average of bonds included in EMBI. Market capitalization is sum of total market value of bonds included in EMBI.

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008 (Aug)	1995-2008 (Aug)
Yield spread over U.S. Treasury (%)	7.96	9.89	7.10	7.87	7.04	5.17	4.13	3.08	2.03	2.02	3.02	5.48
	(25.7)	*(8.3)*	*(3.4)*	*(7.0)*	*(7.5)*	*(6.4)*	*(2.8)*	*(3.7)*	*(1.0)*	*(2.5)*	*(1.3)*	*(20.9)*
Percentage quoted bid/ask spread (%)	1.01	0.97	0.71	0.88	0.85	0.71	0.65	0.58	0.49	0.51	0.64	0.69
	(4.9)	*(1.6)*	*(0.7)*	*(1.3)*	*(1.2)*	*(0.5)*	*(0.7)*	*(0.6)*	*(0.3)*	*(0.6)*	*(0.3)*	*(2.2)*
Total return (%)	-11.63	20.05	13.41	4.37	11.91	22.81	12.80	10.93	8.65	6.06	0.79	166.31
Bond maturity (year)	13.23	12.58	13.09	12.99	11.93	11.39	11.33	11.93	12.64	12.99	13.15	12.45
Modified duration (year)	5.86	5.11	5.48	5.58	5.58	6.06	6.22	6.73	7.18	7.38	7.36	6.19
Average coupon (%)	6.87	7.31	8.37	8.24	8.15	8.25	8.27	8.27	8.14	8.06	7.99	7.99
Market capitalization (billion U.S. dollar)	171.5	167.5	187.7	193.5	188.5	226.4	248.7	278.1	291.0	295.1	291.5	208.2

2.3.2 Liquidity-adjusted CAPM with sovereign bond portfolios

For our methodology, we extend the LCAPM framework developed by Acharya and Pedersen (2005), which examines all four potential channels for a liquidity premium (both individual liquidity and market liquidity) to the bond market. Acharya and Pedersen (2005) show how the CAPM in the imagined frictionless economy translates into a CAPM in net returns for the original economy with illiquidity costs. The one-beta CAPM in net returns can be re-written in terms of gross returns. It introduces three liquidity betas and the expected net return of asset *i* is

$$E_t(r_{t+1}^i - c_{t+1}^i) = r_t^f + \lambda_t \frac{\text{cov}_t(r_{t+1}^i - c_{t+1}^i, r_{t+1}^M - c_{t+1}^M)}{\text{var}_t(r_{t+1}^M - c_{t+1}^M)}, \tag{2.1}$$

where c_t is the relative illiquidity cost at time *t* (i.e., the security illiquidity cost divided by security price), $r^f{}_t$ is the risk-free rate and $\lambda_t = E_t(r^M{}_{t+1} - c^M{}_{t+1} - r^f{}_t)$ is the risk premium. Superscripts *i* and *M* represent the asset *i* and aggregate market respectively. Equivalently, the conditional expected gross return is

$$\begin{aligned} E_t(r_{t+1}^i) = r_t^f + E_t(c_{t+1}^i) + \lambda_t \left\{ \frac{\text{cov}_t(r_{t+1}^i, r_{t+1}^M)}{\text{var}_t(r_{t+1}^M - c_{t+1}^M)} \right\} + \lambda_t \left\{ \frac{\text{cov}_t(c_{t+1}^i, c_{t+1}^M)}{\text{var}_t(r_{t+1}^M - c_{t+1}^M)} \right\} \\ - \lambda_t \left\{ \frac{\text{cov}_t(r_{t+1}^i, c_{t+1}^M)}{\text{var}_t(r_{t+1}^M - c_{t+1}^M)} \right\} - \lambda_t \left\{ \frac{\text{cov}_t(c_{t+1}^i, r_{t+1}^M)}{\text{var}_t(r_{t+1}^M - c_{t+1}^M)} \right\}. \end{aligned} \tag{2.2}$$

Note that covariance and variance terms in the four brackets are equivalent to betas. Therefore, the conditional expected gross return is

$$E_t(r_{t+1}^i) = r_t^f + E_t(c_{t+1}^i) + \lambda_t \beta^{1,i} + \lambda_t \beta^{2,i} - \lambda_t \beta^{3,i} - \lambda_t \beta^{4,i}. \tag{2.3}$$

Equation (2.3) investigates all potential channels for a liquidity premium, which simply state that the required excess security return is the expected relative illiquidity cost, $E_t(c^i_{t+1})$, plus four betas (covariances) multiplied by a risk premium, λ_t. A security might have to pay a premium to compensate for its particular illiquidity or transaction costs, $E_t(c^i_{t+1})$, but this is the least interesting effect.[21] The four betas depend on the asset's payoff and liquidity risk. They are:

1. As in the standard CAPM, the required return on an asset increases linearly with the market beta, $\beta^{1,i}$, i.e., with the covariance between the asset return and the market return.
2. The model also yields three additional effects, which could be regarded as three forms of liquidity risks. The first liquidity beta, $\beta^{2,i}$, is generally positive because a security generally becomes more liquid when the market becomes more liquid. The model implies that expected return increases with the covariance between an asset's illiquidity and the market illiquidity because investors want to be compensated for holding a security that becomes illiquid when the market in general becomes illiquid. Previous studies by Chordia et al. (2000), Hasbrouck and Seppi (2000) and Huberman and Halka (2001) confirm this commonality in liquidity.
3. The second liquidity beta, $\beta^{3,i}$, which measures the exposure of asset *i* to market-wide illiquidity, is usually negative because a rise in market illiquidity reduces asset values. This beta affects required returns negatively because investors are willing to accept a lower return on an asset with a high return in times of market

[21] As mentioned in the Session 2.2 (Related Literature), this is simply the effect of the individual security characteristics on the asset returns.

illiquidity. Consequently, the more negative is the exposure of the asset to market illiquidity, the greater is the required return. This is the main mechanism that Pastor and Stambaugh (2003) and Martinez et al. (2005) investigate.

4. The last liquidity beta, $\beta^{4,i}$, is also negative for most securities. This liquidity beta has a negative sign in the pricing model, meaning that the required return is higher if the sensitivity of the security's illiquidity to market condition is more negative. The negative effect stems from the willingness of an investor to accept lower returns on a security that is liquid in a down market. When the market declines, investors are poor and the ability to sell easily is especially valuable. Hence, an investor is willing to accept a discounted return on a stock with low illiquidity cost in states of poor market return. The effect of this liquidity risk is the most important one reported in Acharya and Pedersen's (2005) results and has not been studied before for emerging-markets bonds.

We have to obtain the unconditional LCAPM under the assumption of independence over time of returns and illiquidity costs. However, liquidity is empirically persistent.[22] It is therefore important to rely on an assumption of constant conditional covariance of innovations in liquidity and returns. Under such an assumption, the "unconditional" CAPM version has the following specification:[23]

$$E(r_t^i - r_t^f) = E(c_t^i) + \lambda\beta^{1,i} + \lambda\beta^{2,i} - \lambda\beta^{3,i} - \lambda\beta^{4,i}, \tag{2.4}$$

where

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[22] This is reported by Hasbrouck and Seppi (2001), Huberman and Halka (2001), Amihud (2002), Pastor and Stambaugh (2003) and Korajczyk and Sadka (2008).

[23] It is unconditional in the sense that the model is independent from time-variation.

$$\beta^{1,i} = \frac{\operatorname{cov}(r_t^i, r_t^M - E_{t-1}(r_t^M))}{\operatorname{var}(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])},$$
$$\beta^{2,i} = \frac{\operatorname{cov}(c_t^i - E_{t-1}(c_t^i), c_t^M - E_{t-1}(c_t^M))}{\operatorname{var}(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])},$$
$$\beta^{3,i} = \frac{\operatorname{cov}(r_t^i, c_t^M - E_{t-1}(c_t^M))}{\operatorname{var}(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])},$$
$$\beta^{4,i} = \frac{\operatorname{cov}(c_t^i - E_{t-1}(c_t^i), r_t^M - E_{t-1}(r_t^M))}{\operatorname{var}(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])}, \tag{2.5}$$

where $r^i{}_t$, $r^f{}_t$ and $r^M{}_t$ are returns on security i, risk-free security and market portfolio. c^i and c^M are the illiquidity costs of security i and the market respectively. $\lambda = E(\lambda_t) = E(r^M{}_t - c^M{}_t - r^f{}_t)$ is the risk premium.

In order to ensure more reliable asset pricing tests, we use forward looking expected spreads after adjusting for default loss, $E(r^i{}_t - r^f{}_t)^*$, rather than average realized excess stock returns as used by Acharya and Pedersen (2005) and most works in asset pricing as a proxy for expected excess returns, $E(r^i{}_t - r^f{}_t)$. If we assume that the risk premium, λ, for all four betas is the same, we can then define the sum of four betas for the net beta ($\beta^{NET,i}$) and the sum of three liquidity betas for liquidity beta sum ($\beta^{LIQ,i}$) as

$$\beta^{NET,i} = \beta^{1,i} + \beta^{2,i} - \beta^{3,i} - \beta^{4,i} \text{ and } \beta^{LIQ,i} = \beta^{2,i} - \beta^{3,i} - \beta^{4,i}. \tag{2.6}$$

We can finally write our unconditional liquidity-adjusted CAPM as

$$E(r_t^i - r_t^f)^* = E(c_t^i) + \lambda\beta^{NET,i} \text{ or} \tag{2.7a}$$

$$E(r_t^i - r_t^f)^* = E(c_t^i) + \lambda\beta^{1,i} + \lambda\beta^{LIQ,i}. \tag{2.7b}$$

From Equation (2.7a), it is clear that expected excess bond returns after adjusting for default loss depend on two components: (i) a security's illiquidity cost c^i, (ii) the covariance of returns with market conditions, $\beta^{NET,i}$. Alternatively if $\beta^{NET,i}$ is taken into two components, we have Equation (2.7b) in which there is market risk ($\beta^{1,i}$) and liquidity risk ($\beta^{LIQ,i}$ or the sum of $\beta^{2,i} - \beta^{3,i} - \beta^{4,i}$). If a security has a higher illiquidity level or transaction cost, an investor required higher expected returns for holding it. The same is applied for a security with higher market and liquidity risks given that the price of risk, λ, is positive or investors are not risk-loving.

In order to test Equations (2.4) and (2.7) in the global bond market context, the assumption that the emerging bond markets have a high degree of integration is crucial and, therefore, the risk in different countries commands the same influence on expected returns.[24] Without such an assumption, the global illiquidity cost (c^M) and global bond market returns (r^M) may not be priced in the cross-section of expected returns. Therefore, comparing across countries, the expected bond returns may not necessarily be higher in a country with a higher level of liquidity risk. If the market is totally segmented, the covariance with the national market portfolio, as opposed to global market portfolio, will solely determine the cross-sectional expected return. Nonetheless, the bond selection criteria for the EMBI ensure the highest possible degree of integration.[25] Asset pricing theory suggests that cross-sectional differences in a country's risk exposures should explain the cross-sectional variation in expected returns.

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[24] We assume that the bond markets are integrated among the emerging markets. If we assume that the emerging U.S. dollar bond markets are fully integrated to the global bond market, the more appropriate benchmark portfolio for measurement of market return and illiquidity cost is the global bond market portfolio, which consists of bonds issued by both emerging and developed countries.

[25] Jun, Marathe and Shawky (2003) report the lower degree of integration with the global economy in the emerging equity markets comparing to the developed-country equity markets. Cumby and Glen (1990) and Harvey (1991) report the world market portfolio beta influences the expected returns in the developed countries.

2.4 Detailed Methodology

This section elaborates on the estimation procedure of the unconditional LCAPM as specified in Equation (2.7) and presents the empirical results. The following steps are implemented and described below is the relevant subsection.

1) At each week t during the study period, data on a percentage quoted bid/ask spread as our measure of illiquidity, c^j_t, is collected for each individual bond j included in the EMBI (Section 2.4.1).
2) A country-specific bond portfolio (i) and market-wide (EMBI) bond portfolio (M) are formed. The returns and illiquidity measures for each portfolio in each week are estimated (Section 2.4.2).
3) For both the country-specific bond portfolio and the market-wide portfolio, the innovations in illiquidity costs and achieved market-wide returns, ($c^i_t - E_{t\text{-}1}(c^i_t)$, $c^M_t - E_{t\text{-}1}(c^M_t)$ and $r^M_t - E_{t\text{-}1}(r^M_t)$), are computed (Section 2.4.3).
4) With these innovations, the liquidity betas can be computed according to Equation (2.5) (Section 2.4.4).
5) Forward-looking expected excess bond returns or $E(r^i_t - r^f_t)^*$, are estimated after correcting for the expected loss (Section 2.4.5).
6) We are then ready to run the cross-section regression in order to test the empirical fit of the unconditional LCAPM in Equation (2.7) using expected returns from spreads (Section 2.5: Empirical Results).

2.4.1 Measuring illiquidity and bond returns

Acharya and Pedersen (2005) in their studying of equities use Amihud's (2002) measure of illiquidity (ILLIQ). This has two shortcomings. First, by construction, this illiquidity measure has a size effect: smaller stocks, which have less amount outstanding for a given same turnover, are automatically more illiquid. This might be one of the reasons why their model is able to explain the portfolio returns sorted by size, but fails to hold for the portfolio sorted by both size and book-to-market. Second, Amihud's measure of illiquidity needs data on trading volume, which is often not available for sovereign bonds.

In the liquidity-related literature, one of the biggest challenges is how to measure liquidity and to some extent how to define liquidity both at individual and at market level. This problem is even worse for studies of liquidity in bond markets, where data are hard to obtain. Since trading volumes in bond markets are usually unavailable, volume-based measures of illiquidity such as trading volume, turnover, ILLIQ and latent liquidity measures cannot be obtained.[26] Fortunately, with our MorganMarket database, the percentage quoted bid/ask spread of the emerging-markets bonds can be gathered on a daily basis. Fleming (2003) and D'Souza, Gaa and Yang (2003) support the bid/ask spread as the most appropriate liquidity indicator because of its high degree of correlation with other measures. Goldreich, Hanke and Nath (2005) suggest that quoted bid/ask spread is a better proxy for liquidity than effective spread (bid/ask spread immediately before each trade) in term of the explanatory power over bond yields.

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[26] Latent liquidity is a very recently developed measure of liquidity based on the bond's accessibility to dealers is developed by Chacko (2006). It is defined as the weighted average turnover of funds holding a particular bond. The volume data from the year 2000 are available for Eurozone sovereign bonds, which are traded via the MTS Global Market bond trading system. The MTS data are essentially the European equivalent of the U.S. GovPX data. However, using these data will greatly reduce the number of countries included in the cross-sectional analysis.

Another important advantage of the bid/ask spread over the ILLIQ measure of illiquidity is that it directly measures the percentage cost incurred, while the ILLIQ measure the percent of return change per one unit of dollar trading volume. Moreover, it is relatively more stationary because there is no effect of inflation that is embedded in the trading. As such, the bid/ask spread can directly enter into the asset pricing function.[27] As opposed to trading volume, the bid/ask spread monotonically increases with illiquidity. For example, even though, trading volume can be very high during a period of crisis, the bid/ask spread is still high and reflects the cost of transaction.

At each week *t* during the study period, a measure of illiquidity or percentage quoted bid/ask spread, c^j_t, is collected for each individual bond *j*, which is included in the EMBI. Where c^j_t is the ratio of the quoted bid/ask spread to the bid/ask midpoint. Weekly estimates are obtained as a simple average through the week as follows:

$$c_t^j = \frac{1}{n_t^j} \sum_{j=1}^{n_t^j} \frac{Ask_t^j - Bid_t^j}{Mid_t^j}, \tag{2.8}$$

where $Mid_t^j = (Ask_t^j + Bid_t^j)/2$, Ask_t^j and Bid_t^j are mid, ask and bid quoted prices of bond *j* in week *t* and n^j_t is the number trading days in week *t* (normally $n^j_t = 5$).[28] The total returns for an individual bond between period t–1 and t is calculated as shown below:

$$r_t^j = \left(\frac{P_t^j + AI_t^j + Coupon_t^j}{P_{t-1}^j + AI_{t-1}^j} \right) - 1, \tag{2.9}$$

[27] In Acharya and Pedersen (2005), ILLIQ is normalized and adjusted for the inflation effect.

[28] Trading days are based on U.S. calendar.

where r^j_t is total return of bond *j* at week *t* incorporating principal and interest, P^j_t is closing clean price for the bond *j* at week *t*, AI^j_t is accrued interest, which is the coupon payment scaled by the ratio of days since the last payment date to the days between last payment and next payment and $Coupon^j_t$ is the coupon payment, if any, of bond *j* at week *t*.

2.4.2 Estimating bid/ask spreads (illiquidity) and returns on bond portfolios

As in other empirical works in asset pricing, grouping the individual securities into portfolios reduces the estimation error. Our test portfolios contain the bonds sorted by the country of issuance. Not only, does such grouping enable the study of liquidity transmission across countries on a global basis, it also provides more convincing results from the statistical perspective. Lewellen, Nagel and Shanken (2010) argue that because of the strong factor structure of size and B/M portfolios, any risk factor is likely to explain the size and B/M effects and one of their suggestions is to sort the test portfolios by other criteria, which are not related to size and B/M. Interestingly, sorting portfolios according to the measure of illiquidity or illiquidity-variation used by Acharya and Pedersen (2005) might still be subject to the size and B/M problem because liquidity and its variation have a close association with size.

Every week *t*, we compute the measure of illiquidity (quoted bid/ask spread) for each individual bond *j* when the bond is available at that time to avoid survivorship bias and average the daily bid/ask spread during the five U.S. working days (Monday to Friday) to reduce noise and sampling errors. The measure of illiquidity of the country portfolio *i* and market-wide portfolio *M* is calculated as follows:

$$c_t^i = \sum\nolimits_{\mathrm{j\ in\ i}} w_t^{ji} c_t^j, \tag{2.10a}$$

$$c_t^M = \sum\nolimits_{i \text{ in } M} w_t^{iM} c_t^i, \tag{2.10b}$$

where w_t^{ji} is the bond j weight for country portfolio i at week t and w_t^{iM} is the country portfolio i weight for market-wide portfolio M. We focus on the market-value weighting.[29] Similarly the return including coupon payment of a portfolio i and market-wide return is computed as

$$r_t^i = \sum\nolimits_{j \text{ in i}} w_t^{ji} r_t^j, \tag{2.11a}$$

$$r_t^M = \sum\nolimits_{i \text{ in } M} w_t^{iM} r_t^i. \tag{2.11b}$$

Note that the unobservable nature of the market portfolio is always a potential problem embedded in the asset pricing test. The market portfolio in this paper is formed by the sovereign bonds issued by emerging markets, which should be a better proxy for the "true" market portfolio than the market portfolio consisting only of highly liquid U.S. equities such as S&P500, NYSE, AMEX or NASDAQ, which have commonly been used in the previous literature since the bond market stands in between the most liquid instruments (e.g., U.S. stocks) and least liquid assets (e.g., real estate or human capital). Value-weighting also ensures investability of the test and market portfolios.

2.4.3 Computing innovations in illiquidity and returns

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[29] Using equal weighting is the way to compensate the over-representing of liquid instruments as compared to true market portfolio, which consists of less-liquid instruments such as small corporate bonds or real estates. However, the problem of over-representation is more severe when the asset class only consists of equities.

As mentioned earlier, liquidity is highly persistent. In order to compute the liquidity betas according to Equation (2.5), we compute innovations in illiquidity costs for the country portfolio and market-wide portfolio and innovations in market-wide returns, $c^i_t - E_{t-1}(c^i_t)$, $c^M_t - E_{t-1}(c^M_t)$ and $r^M_t - E_{t-1}(r^M_t)$, with an autoregressive (AR) process. The residuals from the AR process capture these innovations and are assumed to be *i.i.d.* random variables.

We follow Pastor and Stambaugh (2003) and Acharya and Pedersen (2005), who employ an AR specification with 2-month lags to compute the liquidity innovation for both the market portfolio and all the test portfolios. As weekly data are used in our analysis, we use an AR specification with 8-week lags to capture these innovations.[30] This AR(8) specification for market illiquidity provides an R^2 of 90% and a standard deviation of residuals of 0.10%. The autocorrelation of these residuals is very low at 0.01 and they appear stationary (when 36 lags are included). The estimated innovations in market illiquidity (not tabulated here) are high during periods of liquidity crises in emerging countries, including the Mexican Peso devaluation (December 1994), the Asian Crisis (1997), the Russian Ruble devaluation (August 1998), the LTCM crisis (September 1998), the Brazilian Real devaluation (January 1999), the Turkish Lira devaluation (March 2001) and Argentina’s debt moratorium (December 2001).

2.4.4 Computing liquidity betas

With these innovations (from Section 2.4.3) and Equation (2.5), Table 2-2 reports all four betas, average quoted bid/ask spreads and average expected excess returns using all

[30] An AR specification with 2-week and 4-week lags gives similar results. We also try an autoregressive moving average (ARMA) process and the results do not change.

Table 2-2: Country portfolio characteristics: betas, bid/ask spreads and expected excess returns

In addition to traditional CAPM market beta, $\beta^{1,i}$, three possible different forms of liquidity risk (liquidity betas) for an asset are: (i) commonality in liquidity with the market liquidity, $\beta^{2,i}$, (ii) return sensitivity to market liquidity, $\beta^{3,i}$, (iii) liquidity sensitivity to market returns, $\beta^{4,i}$. $\beta^{NET,i} = \beta^{1,i} + \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$ and $\beta^{LIQ,i} = \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$. $E(c^i_t)$ is the average quoted bid/ask spread for country *i*. $E(r^i_t - r^f_t)^*$ is annual expected excess bond returns after correcting for expected loss at default and subtracting U.S. Treasury bond yields of the same maturity. Countries are sorted according to their values of $\beta^{LIQ,i}$.

Country	$\beta^{1,i}$	$\beta^{2,i}$	$\beta^{3,i}$	$\beta^{4,i}$	$\beta^{NET,i}$	$\beta^{LIQ,i}$	$E(c^i_t)$	$E(r^i_t - r^f_t)^*$
Ghana	0.48	0.05	-0.03	0.13	0.44	-0.04	0.98	0.11
El Salvador	4.05	0.03	-0.19	0.26	4.01	-0.04	1.04	1.34
Hungary	1.62	0.00	0.01	-0.01	1.62	0.00	0.38	0.77
Chile	6.12	0.00	-0.03	0.01	6.15	0.03	0.65	1.42
Trinidad	0.01	0.01	-0.01	-0.02	0.06	0.05	0.65	2.10
Kazakhstan	4.34	0.01	-0.06	0.01	4.39	0.05	1.67	3.35
Serbia	4.62	0.03	-0.16	0.07	4.74	0.12	1.06	0.98
Vietnam	4.12	0.00	-0.14	-0.11	4.37	0.25	0.61	0.52
Indonesia	5.74	0.02	-0.18	-0.09	6.02	0.29	0.72	0.53
Tunisia	5.83	0.02	-0.11	-0.27	6.22	0.40	0.96	1.22
Gabon	0.81	0.03	-0.13	-0.24	1.21	0.40	1.00	2.30
Jamaica	2.73	0.00	-0.13	-0.30	3.17	0.44	0.95	0.69
Sri Lanka	-0.28	-0.05	-0.24	-0.27	0.18	0.46	1.98	3.16
Lebanon	1.20	0.07	-0.08	-0.33	1.68	0.48	1.39	1.32
Egypt	6.97	0.02	-0.28	-0.17	7.45	0.48	0.97	1.16
Pakistan	6.77	0.03	-0.34	-0.27	7.41	0.64	1.50	1.99
Dominican	10.13	0.02	-0.22	-0.47	10.84	0.71	1.37	1.69
China	7.09	0.04	-0.19	-0.55	7.87	0.78	0.62	1.04
Greece	6.68	0.08	-0.37	-0.40	7.53	0.86	0.48	0.86
Ukraine	12.72	0.06	-0.49	-0.59	13.87	1.14	0.82	3.89
Poland	24.43	0.10	-0.76	-1.06	26.35	1.92	0.63	1.56
Korea	24.10	0.12	-0.87	-1.02	26.11	2.01	0.58	1.59
Uruguay	25.41	0.10	-0.66	-1.30	27.46	2.05	1.71	2.09
Belize	1.80	0.06	-0.21	-1.80	3.87	2.07	3.02	2.15
Morocco	53.92	0.07	-1.91	-0.29	56.18	2.27	0.86	3.37
Mexico	39.66	0.11	-1.05	-1.13	41.95	2.29	0.46	3.15
Thailand	31.13	0.23	-1.32	-1.32	34.00	2.87	1.03	1.47
Malaysia	16.99	0.13	-0.64	-2.12	19.88	2.90	0.78	1.76
Philippines	28.75	0.14	-1.28	-1.66	31.83	3.08	0.80	2.67
Columbia	30.20	0.18	-1.27	-1.83	33.48	3.28	0.84	3.21
Argentina	65.99	0.19	-2.05	-1.45	69.68	3.69	1.37	14.53
Panama	43.01	0.25	-1.21	-2.45	46.92	3.91	0.79	2.13
Venezuela	58.71	0.16	-1.60	-2.17	62.64	3.93	0.71	4.51
Turkey	35.87	0.24	-1.15	-2.59	39.84	3.97	0.79	1.61
Brazil	71.99	0.16	-2.23	-2.13	76.50	4.51	0.63	4.31
South Africa	19.35	0.23	-0.74	-3.85	24.18	4.83	0.91	1.68
Bulgaria	63.93	0.21	-2.12	-2.78	69.05	5.12	0.85	3.56
Peru	50.40	0.28	-2.07	-2.84	55.58	5.19	1.41	2.90
Ecuador	83.63	0.28	-2.65	-2.97	89.53	5.90	1.18	6.53
Russia	105.44	0.27	-3.90	-2.91	112.53	7.09	0.69	6.44
Nigeria	49.36	0.61	-2.09	-6.47	58.54	9.18	2.88	8.91
Croatia	45.40	0.61	-1.82	-11.36	59.19	13.79	1.06	3.01

available time-series data.[31] The table is sorted in ascending order of estimated sum of liquidity betas ($\beta^{LIQ,i}$). In the table, country portfolios, which have higher market betas, liquidity betas and quoted bid/ask spreads, tend to have greater expected excess returns.

Note, however, that more illiquid portfolios (higher quoted bid/ask spreads) do not always have a higher level of liquidity risk (higher liquidity betas). A country with high illiquidity costs may enjoy low costs of borrowing if its bonds have low covariance with global factors: international investors require lower returns for holding them since they consider them to be a hedging instrument.

Table 2-3 shows that there is a high degree of correlation across the different measures of liquidity risk. It is therefore difficult to distinguish empirically the effects of each liquidity beta. Assuming that the risk premium, λ, for all four betas is the same and defining the sum of four betas as the net beta ($\beta^{NET,i}$) as in Equation (2.6) will help alleviate this statistical problem. Table 2-5 also shows that the cross-sectional correlation between the net beta and expected cost of illiquidity is very low (–0.04), so grouping betas in this way makes sense statistically.

Table 2-3: Beta correlations for country portfolios

We report correlations of $\beta^{1,i}$, $\beta^{2,i}$, $\beta^{3,i}$ and $\beta^{4,i}$ for the 42 value-weighted country portfolios. The collinearity of measure of liquidity risks makes it hard to measure the impact of each beta separately.

	$\beta^{1,i}$	$\beta^{2,i}$	$\beta^{3,i}$	$\beta^{4,i}$
$\beta^{1,i}$	1.00	0.65	-0.98	-0.52
$\beta^{2,i}$		1.00	-0.71	-0.93
$\beta^{3,i}$			1.00	0.57
$\beta^{4,i}$				1.00

[31] How to estimate the expected excess bond returns is outlined in Section 2.4.5. The scale of betas may not seem realistic at the first glance. For example, Russia has a market beta of around 100. However, it makes senses because the betas are calculated from innovations in liquidity and returns rather than their level. Acharya and Pedersen (2005) also report the betas of similar magnitude.

2.4.5 Constructing the expected bond returns

Expected bond returns are computed by a method similar to that used by De Jong and Driessen (2006) and Campello et al. (2008). The following equation is used to calculate the expected bond returns:

$$E(r_t^i - r_t^f)^* = (y_t^i - r_t^f) + EDL_t^i + ERND_t^i, \tag{2.12}$$

where $E(r^i_t - r^f_t)^*$ is the expected bond excess return, r^f_t is the risk-free rate, y^i_t is the yield to maturity given that there is no change in bond yield, EDL^i_t or expected default loss rate is defined as −default probability · (1− recovery rate)/dt < 0 and $ERND^i_t$ or expected return due to yield change conditional on no-default. In Equation (2.12), we ignore this $ERND^i_t$ term because Campello et al. (2008) stress that it is on average very small and De Jong and Diessen (2005) also ignore this term.

We start by computing bond yield spread subtracting U.S. Treasury bond yield of the same maturity, $y^i_t - r^f_t$. Then expected default loss rate, EDL^i_t, is calculated using the default probability and recovery rate provided by Standard & Poor's. In computing default probability, we obtain the long-term foreign-currency sovereign credit rating and its one-year transition rates from Standard & Poor's.[32] We estimate the maturity-matching default probability under Markov chain with an absorbing state (i.e., default state). The default probability data are available for the entire sample period and for all countries included in the EMBI. In computing the recovery rate, we use the recovery rate applied from recovering rating issued to 25 speculative-grade sovereign issuers

[32] Please see Standard & Poor's, Sovereign Rating History Since 1975, published on 3 January 2007 for credit ratings and Sovereign Defaults and Rating Transition Data: 2006 Update, published on 1 February 2007 for one-year transition rates.

published by Standard & Poor's.[33] In assigning the recovery rating, Standard & Poor's considers three major aspects: 1) the sovereign's ability to resume payments after default, 2) the sovereign's recovery incentives and 3) the impact of official creditors. For other sovereigns for which the recovery rating is not available, the recovery rate for corporate bonds provided by Alman and Kishore (1998) (which are the following; 68.34% for AAA, 59.59% for AA, 60.63% for A, 49.42% for BBB, 39.05% for BB, 37.54% for B, and 38.02% for CCC bonds) are used for the expected bond returns estimation.[34] Finally if the estimated $E(r^i_t - r^f_t)^*$ for any week t is less than zero, it is replaced by zero value. After correcting for expected loss, the bond market should provide a cleaner (less noisy) ex ante expected return than the stock market and should deliver reliable empirical results without needing very long time-series data. The statistics of expected excess bond returns, estimated betas and percentage quoted bid/ask spreads by sovereign are reported in Table 2-2.

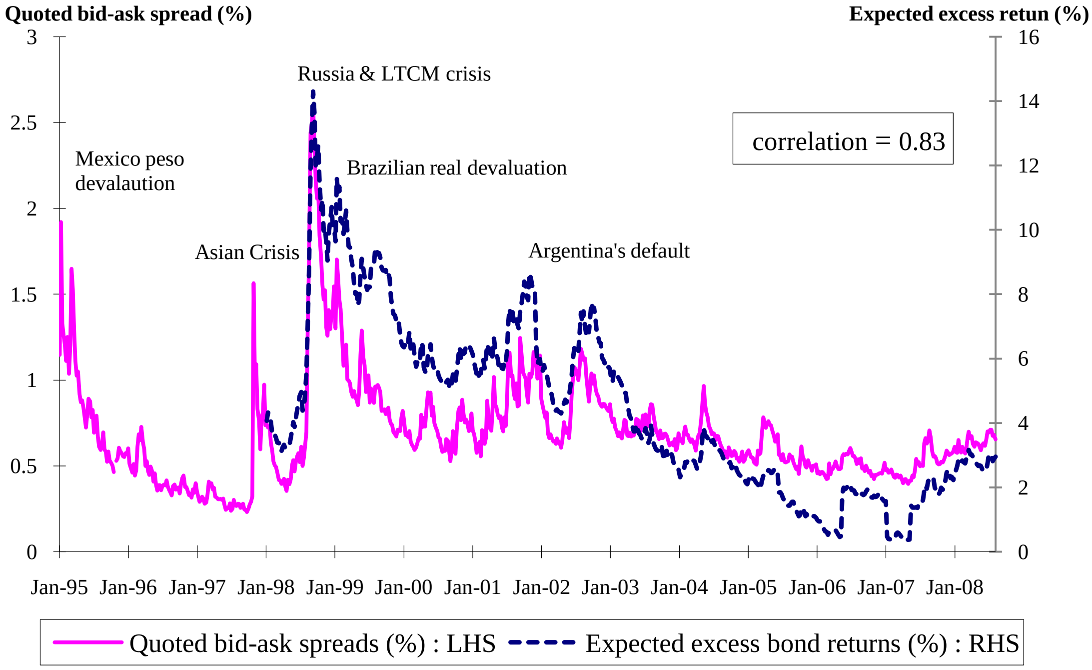
Time series of percentage quoted bid/asks spreads calculated as in Section 2.4.2 and expected excess returns of the EMBI, which represent the market-wide or global portfolio, are shown in Figure 2-2. Note that the spreads and expect excess returns move very closely to each other. As expected, both increase sharply during periods of financial turmoil.

[33] Twenty-five speculative sovereign issuers consist of Argentina, Belize, Brazil, Columbia, Costa Rica, Dominican, Ecuador, Egypt, El Salvador, Grenada, Guatemala, Indonesia, Jamaica, Lebanon, Macedonia, Pakistan, Panama, Peru, Philippines, Serbia, Turkey, Ukraine, Uruguay, Venezuela and Vietnam. The recovering rating of 1, 2, 3, 4 and 5 implies the recovery rate of 95%, 80%, 60%, 40% and 20% respectively. See article titled "Introduction of Sovereign Recovery Ratings" published on June 12, 2007 for more detail.

[34] Elton et al. (2001) and Campello et al. (2008) also use this recovery rate. Using only the recovery rate by Alman and Kishore (1998) also gives the similar empirical results.

Figure 2-2: Time series of weekly market-wide (EMBI) percentage quoted bid/asks spreads and expected excess returns

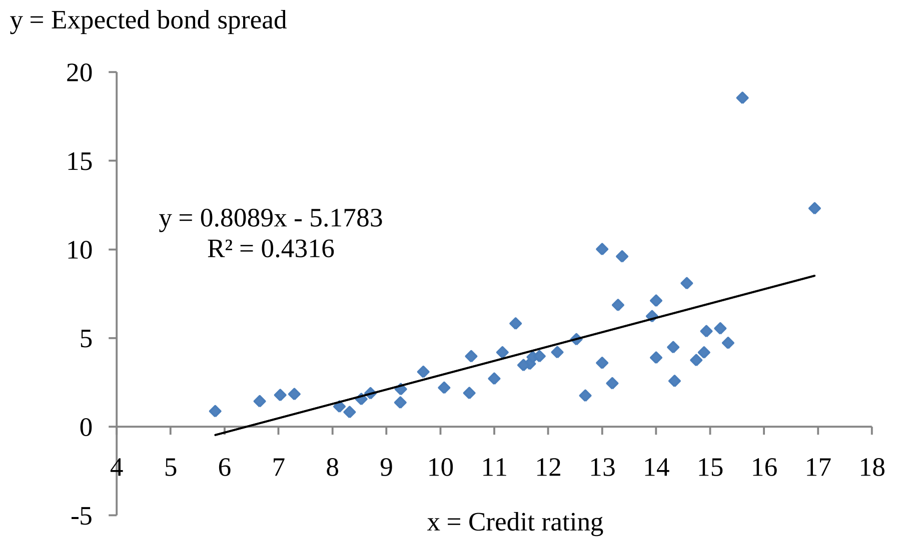
This figure shows time series of quoted bid/asks spreads calculated as in Section 2.4.2 and expected excess returns calculated as in Section 2.4.5 of the EMBI, which represents the market-wide or global portfolio. Percentage quoted bid/ask spread is calculated as, (quoted ask price_t^{EMBI} – quoted bid price_t^{EMBI})/ mid price_t^{EMBI}, which reflects illiquidity cost of the overall international bond markets. The expected excess bond return, $E(r^i_t - r^f_t)^*$, is bond yields after correcting for expected loss at default and subtracting U.S. Treasury bond yields of the same maturity. The market portfolio is formed using the value weighting method. Events, which significantly impacted global liquidity level and the global expected bond returns, are also depicted in the figure. Two series report a correlation of 0.83.



In general, lower credit rating bonds command higher expected spreads over risk-free rates. However, if expected bond spreads are adjusted for their default loss and illiquidity cost, we should not expect to find a strong relationship between credit ratings and expected bond spreads. Figure 2-3 shows the relationship between average credit rating and average expected bond spread before and after adjusting for expected default loss and illiquidity cost for each country's bond portfolio during our sample period. In the calculation, we use our computed percentage quoted bid/ask spread as a proxy for illiquidity cost and adjust default loss as outlined above. In addition, the lower panel of

Figure 2-3: Relationship between expected bond spread and credit rating

The upper panel plots the average expected bond spread against average credit rating for each country's bond portfolio during January 1995 to August 2008. The lower panel plots the average expected bond spread after adjusting for default loss and illiquidity cost (bid/ask spread) against average credit rating for each country's bond portfolio during January 1995 to August 2008. The expected bond spread is equal to the difference between the average yield to maturity in the emerging country and the corresponding yield to maturity on the U.S. Treasury spot curve, after 'stripping' out the value of any collateralized cash flows. The expected bond spread after adjusting for default loss and illiquidity cost is the bond spread minus expected loss and recovery if default occurs and minus illiquidity cost. Illiquidity cost is percentage quoted bid/asks spread. Standard & Poor's Rating is an integer representation of each country's rating with 1 assigned to AAA and 21 assigned to C. The fitted solid lines are from OLS regression. Its regression results are also reported.



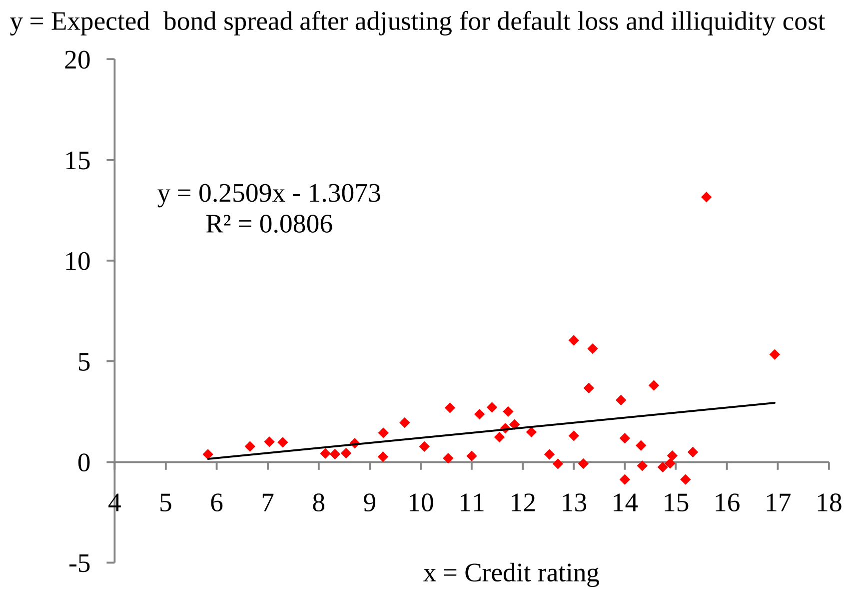


Figure 2-3 suggests that potential sovereign bond default, as represented by credit rating, alone cannot explain credit spreads in emerging-markets' sovereign bonds. Bond duration does not also help to explain the cross-section of average expected bond spread (results are not reported here). Our findings are consistent with Gebhardt, Hvidkjaer and Swaminathan (2005) that corporate bond characteristics such as credit rating and duration are less important than systematic risk factors as far as bond returns are concerned. The systematic risks such as market risk and liquidity risk may be more important.[35]

[35] Because of our focus in the LCAPM of Acharya and Pedersen (2005), we do not include the default risk in this paper. However, the second research paper in Chapter 4 shows that the liquidity risk is still important for bond prices after controlling for the default risk.

2.5 Empirical Results: Cross-sectional Regression of LCAPM

In this section, we employ two estimation methods in testing our 42 sovereign bond portfolios. One is a cross-sectional regression of the unconditional LCAPM, using data for the whole available sample (data from Table 2-2). The other is a weekly Fama-MacBeth regression using historical 5-year rolling data to compute all betas according to Equation (2.5). These two different methods provide a chance to examine the robustness of our results. Both give similar results at the end.

2.5.1 Single cross-sectional regression of unconditional LCAPM

From Table 2-2, we are now ready to run the cross-section regression in order to test the empirical fit of the unconditional LCAPM in Equation (2.7). Equivalently, we investigate whether cross-sectional differences in average risk explain the differences in average expected returns of sovereign bonds in emerging markets. Table 2-4 reports the regression results, where standard errors are computed using the Newey and West (1987) method. We run seven different cross-sectional regressions.

Model 4.1 in Table 2-4 is a regression containing only the standard market beta. Basically, it is the standard CAPM equation. As expected, the risk premium, λ, is positive and significant. However, the constant or pricing error is also positive and significant.

Models 4.2 and 4.3 present the results for regressions that include the quoted bid/ask spread, $E(c^i_t)$, and a net beta, ($\beta^{NET,i} = \beta^{1,i} + \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$). The LCAPM implies that the coefficient of $E(c^i_t)$ should be positive, to adjust for the difference between

Table 2-4: Country portfolios and cross-sectional regression

This table reports results from the cross-sectional regression of the unconditional LCAPM in Equation (2.7) for 42 value-weighted country portfolios using weekly data during January 1995 to July 2008 with a value-weighted market portfolio. Specifications, which are considered, are alternative cases of the following equation:

$$E(r_t^i - r_t^f)^* = \alpha + \omega E(c_t^i) + \lambda^1\beta^{1,i} + \lambda^2\beta^{2,i} + \lambda^3\beta^{3,i} + \lambda^4\beta^{4,i} + \lambda^5\beta^{NET,i} + \lambda^6\beta^{LIQ,i},$$

where $E(r^i_t - r^f_t)^*$ is the average expected excess return for country *i*. $E(c^i_t)$ is the average quoted bid/ask spread. $\beta^{1,i}$ is the market beta, $\beta^{2,i}$, $\beta^{3,i}$ and $\beta^{4,i}$ represent three liquidity betas. $\beta^{NET,i} = \beta^{1,i} + \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$ and $\beta^{LIQ,i} = \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$. Betas are pre-estimated using Equation (2.5). In some specification, ω is set to be the average weekly turnover ($\omega = 0.04$ or annual turnover of about two). The t-statistics from Newey and West (1987) heteroskedasticity-consistent standard error & covariance least square regression are in the parentheses. R^2 and Adjusted R^2 are reported in the last column. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively.

	constant (α)	$E(c^i_t)$	$\beta^{1,i}$ Cov(r^i,r^M)	$\beta^{2,i}$ Cov(c^i,c^M)	$\beta^{3,i}$ Cov(r^i,c^M)	$\beta^{4,i}$ Cov(c^i,r^M)	$\beta^{NET,i}$ Sum of 4 betas	$\beta^{LIQ,i}$ Liquidity Beta sum	R^2 (adj-R^2)
4.1	0.0181[c]		0.0013[c]						0.45
	(3.88)		(4.58)						(0.44)
4.2	-0.0250[c]	0.0400					0.0012[c]		0.51
	-(4.01)	(-)					(4.94)		(0.50)
4.3	-0.0133	0.0290[c]					0.0012[c]		0.56
	-(1.12)	(2.72)					(4.88)		(0.54)
4.4	-0.0241[c]	0.0400	0.0024[c]	0.0934	0.0313	0.0075			0.56
	-(4.41)	(-)	(2.87)	(1.17)	(1.38)	(1.45)			(0.51)
4.5	-0.0173	0.0332[b]	0.0022[a]	0.1049	0.0269	0.0075			0.59
	-(1.24)	(2.43)	(2.01)	(1.11)	(0.99)	(1.49)			(0.54)
4.6	-0.0098	0.04						0.0075[c]	0.19
	-(1.24)	(-)						(2.78)	(0.17)
4.7	0.0101	0.0193						0.0082[c]	0.29
	(1.14)	(1.62)						(3.00)	(0.26)

estimation periods (weekly) and investors' holding periods. In model 4.2, the coefficient of $E(c^i_t)$ is constrained to be 0.04, which is equivalent to the average holding period of about 1/0.04 ≅ 25 weeks or 0.5 year.[36] The risk premium attached to $\beta^{NET,i}$ is positive with correct sign and significant. In model 4.3, when we do not fix the coefficient on $E(c^i_t)$, the estimated coefficient on $E(c^i_t)$ is 0.029 and fairly closed to our calibrated number (0.04). Both significant evidences, that $E(c^i_t)$ in model 4.3 is positive and $\beta^{NET,i}$ is positive in models 4.2 and 4.3, lend support to the LCAPM. In addition, comparing

[36] Unlike stocks, the trading volumes on bond markets are difficult to obtain because bonds are normally traded over-the-counter. Therefore, their data are fragmented and not centralized. The annual average turnover of about two is approximated from Knight (2006).

models 4.1 with 4.2, the adjusted R^2 is higher when liquidity risks are included in the pricing equation, even if we maintain the number of the free parameters (i.e., same degrees of freedom).

The evidence of liquidity risk is weaker when we allow each of the betas to have a different risk premium. In models 4.4 and 4.5, the betas are not very significant because of multicollinearity (see Table 2-3). It is hard to distinguish empirically the significance of liquidity risk versus market risk on expected excess bond returns. Models 4.6 and 4.7 exclude the market beta. The aggregate liquidity beta ($\beta^{LIQ,i} = \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$) is now positive and significant in both models. In conclusion, there is some evidence that liquidity risk and liquidity level are priced.

Table 2-5 indicates low correlations between $E(c^i_t)$ with both $\beta^{NET,i}$ and $\beta^{LIQ,i}$, hence, the multicollinearity problem is less relevant in models 4.3 and 4.7 than other regressions. In general, the results here are consistent with those reported by Acharya and Pedersen (2005) and Lee (2010) for U.S. equity and global equity markets respectively. Although not tabulated here when we include only one particular beta (β^1, β^2, β^3 and β^4) in the cross-sectional regression, it has the correct sign (positive sign for β^1 and β^2 and negative sign for β^3 and β^4) and is significant.

Table 2-5: Correlations of variables in testing the unconditional LCAPM

$E(c^i_t)$ is the average effective bid/ask spread for country *i*. $E(r^i_t - r^f_t)^*$ is expected excess returns. $\beta^{NET,i} = \beta^{1,i} + \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$ and $\beta^{LIQ,i} = \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$. Correlations are reported for the 42 value-weighted country portfolios. $E(c^i_t)$ has a low correlation with both $\beta^{NET,i}$ and $\beta^{LIQ,i}$.

	$E(c^i_t)$	$\beta^{LIQ,i}$	$\beta^{NET,i}$	$E(r^i_t - r^f_t)^*$
$E(c^i_t)$	1.00	0.17	-0.04	0.31
$\beta^{LIQ,i}$		1.00	0.77	0.49
$\beta^{NET,i}$			1.00	0.67
$E(r^i_t - r^f_t)^*$				1.00

Respectively, Panels A, B and C in Figure 2-4 show the empirical fit of the standard CAPM from model 4.1 in Table 2-4, constrained LCAPM from model 4.2 in Table 2-4 and unconstrained LCAPM from model 4.5 in Table 2-4. Liquidity risks improve the fit for both low-yield and high-yield sovereign bond portfolios and the improvement in fit does not result from an increase in the number of explanatory variables in the regression (models 4.1 versus 4.2). Note that Argentina represents an extreme case, with weekly average return of more than 0.25%. However, the result in this section is still the same when Argentinian bond portfolio is excluded.

To summarize, the results are very supportive of the hypothesis that liquidity risk is priced in the international bond market or the cross-sectional differences in average risk can explain the differences in average returns in the international bond market.

2.5.2 Economic significance

Using the empirical results from model 4.2 in Table 2-4 (with λ = 0.0012 and using the six-month holding period, i.e., coefficient of $E(c^i_t)$ or ω is fixed at 0.04), the economic significance of three estimated liquidity risk measures on expected bond returns can be determined. For example, consider Ghanaian and Croatian bond markets for which the difference in unconditional expected excess return is about 2.90% (3.01% – 0.11%) per annum (from Table 2-2, last column) given our model is correctly specified:[37]

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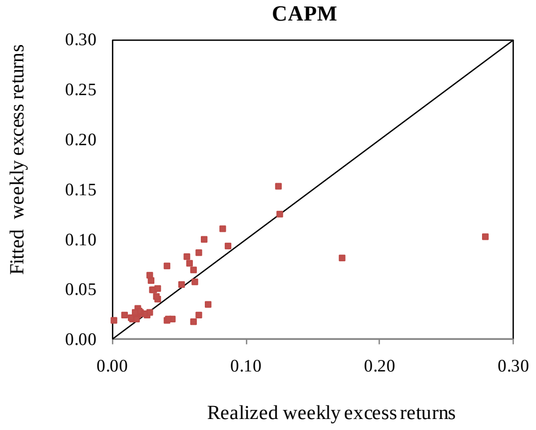
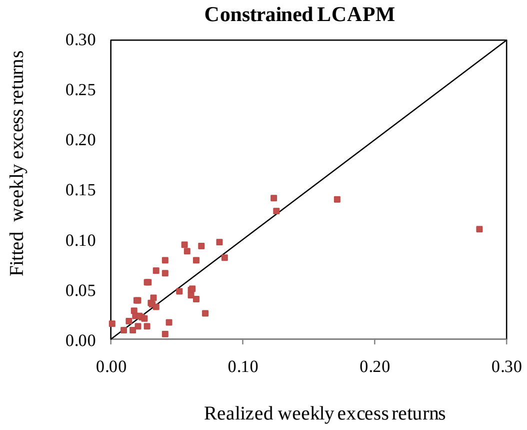
[37] I pick Ghana and Croatia because they are respectively the lowest and highest liquidity risk countries as measured by the magnitude of $\beta^{LIQ,i}$. From Table 2-2, $\beta^{LIQ,Ghana}$ = –0.04 and $\beta^{LIQ,Croatia}$ = 13.79.

Figure 2-4: Empirical fit of CAPM versus LCAPM
Panel A depicts the fitted CAPM returns against realized returns using weekly data from January 1995 to August 2008 for value-weighted country portfolios. Panel B shows the same for the constrained LCAPM and Panel C represents the same for the unconstrained LCAPM.

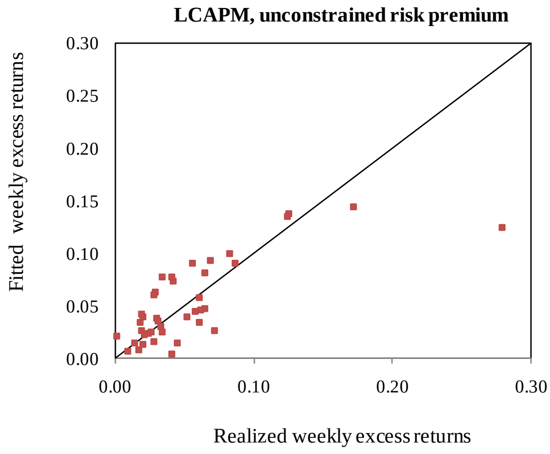
Panel A



Panel B



Panel C



(i) The difference in annualized expected excess returns between those two sovereign bond portfolios that results from the difference in the co-movement between country-specific liquidity and market liquidity, Cov(c^i,c^M) or β^2, is $\lambda \cdot (\beta^{2,Croatia} - \beta^{2,Ghana}) \cdot 52 = 0.03\%$ per annum.

(ii) In a similar manner, the difference in annualized expected excess returns that is due to the difference in the return sensitivity to market liquidity, Cov(r^i,c^M) or β^3, is $-\lambda \cdot (\beta^{3,Croatia} - \beta^{3,Ghana}) \cdot 52 = 0.11\%$ per annum.

(iii) The difference in annualized expected excess returns owing to the difference in the commonality in the country-specific liquidity and market returns, Cov(c^i,r^M) or β^4, is $-\lambda \cdot (\beta^{4,Croatia} - \beta^{4,Ghana}) \cdot 52 = 0.70\%$ per annum.

Hence, the total effect of liquidity risk is 0.84% (0.03% + 0.11% + 0.70%) annually.

(iv) Meanwhile, the difference in annualized expected excess returns that can be attributed to the difference in the expected level of liquidity is estimated (based on historical average turnover) to be $0.04 \cdot [E(c_t^{Croatia}) - E(c_t^{Ghana})] \cdot 52 = 0.16\%$ annually.

Therefore, the combined effects of liquidity risk and liquidity level can explain as much as 1.00% per annum of credit spread or about 35% of the 2.90% difference in spreads between Croatia and Ghana.[38] Interestingly, in terms of credit ratings, Ghana has the average credit rating of B+, whereas Croatia's average credit rating is BBB. Ghana also issues longer-term sovereign bonds (average modified duration of 6.42 year versus 3.42 years). However, Ghana commands lower cost-of-borrowing partly because it is the lowest liquidity-risk country. This finding also indicates that the impacts of liquidity (flight to liquidity) are stronger than those of credit quality (flight to quality) across our set of emerging countries during our study periods (January 1995 to August 2008). International investors require lower expected returns when holding a security that performs well in the times of difficulties. Such effects at times can overcome the risk premium from credit risk and interest rate term risk.

[38] Expected excess returns are 0.11% annually for Ghana's bond portfolio and 3.01% for Croatia's bond portfolio.

In U.S. stock markets, Acharya and Pedersen (2005) find the total effect of liquidity risk is 1.10% per annum and the effect of expected liquidity level is 3.50% annually. Pastor and Stambaugh (2003) and Sadka (2006) report a high illiquidity risk premium between 5% and 7.5%, but they do not take expected liquidity level into account. Since they do not have data on the expected liquidity of U.S. corporate bonds, De Jong and Driessen (2006) do not include an expected liquidity level in the model and they report a liquidity risk premium for CCC bonds of 1.00% per year. In summary, the liquidity risk premium estimated for the emerging U.S. dollar sovereign bond markets are relatively in line with the estimates obtained in the U.S. equity and corporate bond market.

2.5.3 Fama-MacBeth (1973) regression[39]

In the same way as in the previous section, we now study how liquidity risk affects expected bond returns, but using the standard Fama-MacBeth (1973) method for our 42-country bond portfolios and results are reported in this section. We employ the same methodology as in Section 2.4.1 to Section 2.4.5 except that all betas are computed using 5-year rolling data. Four betas are computed using the prior 260 weeks' innovations in returns and illiquidity. Betas are included if they have at least 144 weeks' (36 months') observations of data before the test week. Since we require five years of prior data to estimate betas, our Fama-MacBeth regression uses data from January 2000 to August 2008, even though the sample starts in January 1995. In total, 9,957 data points are included. Standard errors are computed using the Newey and West (1987) method with three lags. The summary statistics of data used and their correlation

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[39] The previous approach that first calculates the mean return for each country bond's portfolio over the sample and then regresses the mean returns on the betas estimated over the same sample period could be problematic because returns are often cross-sectionally correlated and heteroscedastic. Therefore results based on this approach can be misleading.

coefficients are provided in Table 2-6. The data show similar patterns to those used in the single unconditional LCAPM. In Panel B, all individual betas are shown to exhibit a high degree of correlation. We therefore again expect a multicollinearity problem in betas when all betas are individually included in the regression. However, this problem is not an issue when either $\beta^{NET,i}$ or $\beta^{LIQ,i}$ is used as an explanatory variable because of the relatively low correlations between $E(c^i_t)$ and $\beta^{NET,i}$ (as well as $E(c^i_t)$ and $\beta^{LIQ,i}$).

Table 2-6: Summary statistics of data used in Fama-MacBeth regression

These tables report the summary statistics on all data used in Fama-MacBeth regressions (Table 2-6.1) and correlations (Table 2-6.2). The weekly-data sample spans from January 2000 to August 2008. $E(c^i_t)$ is the average quoted bid/ask spread for country *i*. $E(r^i_t - r^f_t)^*$ is expected excess bond returns after correcting for expected loss at default and subtracting U.S. Treasury bond yields of the same maturity. In addition to traditional CAPM market beta ($\beta^{1,i}$), three possible different forms of liquidity risk (liquidity betas) for an asset are: (i) commonality in liquidity with the market liquidity, $\beta^{2,i}$, (ii) return sensitivity to market liquidity, $\beta^{3,i}$, (iii) liquidity sensitivity to market returns, $\beta^{4,i}$. $\beta^{NET,i} = \beta^{1,i} + \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$ and $\beta^{LIQ,i} = \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$. Correlation coefficients in Table 2-6.2 are the time-series average of sectional correlation coefficients. All coefficients are significant at all conventional level (H_0: rho = 0 is all rejected).

Table 2-6.1

Variable	Number of observation	Mean	Standard deviation	Max	Min
$E(c^i_t)$	9,957	0.781	0.613	8.041	0.057
$E(r^i_t - r^f_t)^*$	9,957	2.486	5.851	58.830	0.000
$\beta^{1,i}$	9,957	35.890	29.985	170.226	-0.139
$\beta^{2,i}$	9,957	0.126	0.102	0.723	-0.007
$\beta^{3,i}$	9,957	-1.061	0.867	0.178	-4.641
$\beta^{4,i}$	9,957	-1.300	1.432	1.534	-10.754
$\beta^{NET,i}$	9,957	38.376	31.556	177.225	-0.039
$\beta^{LIQ,i}$	9,957	2.486	2.097	14.130	-0.860

Table 2-6.2

	$E(c^i_t)$	$\beta^{1,i}$	$\beta^{2,i}$	$\beta^{3,i}$	$\beta^{4,i}$	$\beta^{NET,i}$	$\beta^{LIQ,i}$
$E(c^i_t)$	1.000	0.057	0.278	-0.141	-0.061	0.061	0.114
$\beta^{1,i}$		1.000	0.628	-0.926	-0.469	0.999	0.733
$\beta^{2,i}$			1.000	-0.720	-0.693	0.651	0.820
$\beta^{3,i}$				1.000	0.506	-0.933	-0.794
$\beta^{4,i}$					1.000	-0.507	-0.926
$\beta^{NET,i}$						1.000	0.763
$\beta^{LIQ,i}$							1.000

Table 2-7 reports the Fama-MacBeth regression results, most of which are consistent with the results in Table 2-4 from the single cross-sectional regression both in terms of statistical properties and coefficient's magnitudes. Model 7.1 indicates that market risk is significant and positive as expected. Models 7.2 and 7.3 show that $\beta^{NET,i}$ is strongly priced in the emerging sovereign bond markets whether or not the calibrated holding period of about 6 months is imposed. Again because of the multicollinearity in betas, results from models 7.4 and 7.5 are weak. When only liquidity betas, $\beta^{LIQ,i}$, are included in models 7.6 and 7.7, liquidity risk works well in explaining cross-sectional difference of bond returns. When we include one particular beta (β^1, β^2, β^3 and β^4) in the cross-sectional regression, it has the correct sign (positive sign for β^1 and β^2 and negative sign for β^3 and β^4) and it is all significant (not tabulated here). In sum, we find the same evidence as before that investors are compensated for holding emerging-markets' sovereign bonds whose returns are sensitive to the global market factors (both market risk and liquidity risk). We also find that the liquidity level is highly priced in every specification.

Table 2-7: Country portfolios and Fama MacBeth regression

This table reports the time-series of estimated premia from Fama-MacBeth regression based on the unconditional LCAPM in Equation (2.7) for 42 value-weighted country portfolios using weekly data during January 2000 to July 2008 with a value-weighted market portfolio. For each country portfolio, betas are pre-estimated using the previous five years returns and illiquidity. To be included, country portfolio must have at least 144 weekly (or three-year data) innovations in return and illiquidity. Specifications, which are considered, are alternative cases of the following equation:

$$E(r_t^i - r_t^f)^* = \alpha + \omega E(c_t^i) + \lambda^1\beta^{1,i} + \lambda^2\beta^{2,i} + \lambda^3\beta^{3,i} + \lambda^4\beta^{4,i} + \lambda^5\beta^{NET,i} + \lambda^6\beta^{LIQ,i},$$

where $E(r^i_t - r^f_t)^*$ is the average expected excess return for country *i*. $E(c^i_t)$ is the average quoted bid/ask spread. $\beta^{1,i}$ is the market beta, $\beta^{2,i}$, $\beta^{3,i}$ and $\beta^{4,i}$ represent three liquidity betas. $\beta^{NET,i} = \beta^{1,i} + \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$ and $\beta^{LIQ,i} = \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$. Betas are pre-estimated using Equation (2.5). In some specification, ω is set to be the average weekly turnover (ω = 0.04 or annual turnover of about two). The t-statistics from Newey and West (1987) heteroskedasticity-consistent standard error & covariance least square regression are in the parentheses. R^2 and Adjusted R^2 are reported in the last column. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively.

	constant (α)	$E(c^i_t)$	$\beta^{1,i}$ Cov(r^i,r^M)	$\beta^{2,i}$ Cov(c^i,c^M)	$\beta^{3,i}$ Cov(r^i,c^M)	$\beta^{4,i}$ Cov(c^i,r^M)	$\beta^{NET,i}$ Sum of 4 betas	$\beta^{LIQ,i}$ Liquidity Beta sum	R^2 (adj-R^2)
7.1	0.0117[c]		0.0014[c]						0.14
	(4.33)		(10.28)						(0.10)
7.2	-0.0172[c]	0.0400					0.0011[c]		0.13
	-(7.83)	(-)					(10.81)		(0.09)
7.3	-0.0439[c]	0.0859[c]					0.0007[c]		0.41
	-(6.68)	(9.22)					(10.75)		(0.35)
7.4	-0.0065[c]	0.0400	0.0027[c]	0.3114[c]	0.0295[c]	0.0526[c]			0.42
	-(2.70)	(-)	(8.97)	(4.45)	(3.44)	(6.24)			(0.29)
7.5	-0.0363[c]	0.0895[c]	0.0015[c]	-0.1562[c]	-0.0060	0.0245[c]			0.55
	-(6.57)	(9.85)	(6.56)	-(2.65)	-(0.86)	(3.68)			(0.44)
7.6	0.0027	0.04						0.0084[c]	0.03
	(0.94)	(-)						(6.66)	(0.01)
7.7	-0.0349[c]	0.0927[c]						0.0035[c]	0.35
	-(5.38)	(9.01)						(5.28)	(0.29)

2.6 Robustness Tests

In this section, we perform some robustness tests on the results presented above by (i) investigating the bond characteristics in the cross-sectional regression, (ii) analyzing the impact of U.S. stock markets on emerging U.S. dollar sovereign bond markets and (iii) performing the out-of-sample analysis.

2.6.1 Liquidity betas versus bond characteristics in explaining bond returns

We include the bond portfolios' characteristics in our asset pricing equations to test whether they or factor loading (market risk and liquidity risk) are more relevant in explaining the cross-section of excess bond returns. In previous studies (for example, Fama and French (1993) and Gebhardt et al. (2005)), bond credit rating and duration have been used as bond characteristics. They might arguably be better proxies of true unobservable betas than the estimated betas. Credit rating and duration are supposed to be proxies for bond default risk and interest rate term risk. This section therefore incorporates bond portfolios' characteristics (i.e., their credit rating and modified duration) into our cross-sectional LCAPM in Equation (2.7).[40] The main question is whether our liquidity risk is still important after controlling for the systematic default risk and term risk represented by credit rating and duration respectively.

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[40] There are drawbacks of using credit rating to control for default risk. While credit rating contains information about default intensity and loss given default, it may not a sufficient statistic for the true default spread or updated at the same pace as other risk factors. However, our results in Chapter 4 confirm that liquidity effect is still robust when we use the return spread between junk and investment bond portfolios as a proxy for bond default risk. We also experimented with this variable in this chapter as well and the results are still the same. In addition, the results do not change if we also include other characteristics such as amount outstanding scaled by taking natural log (in order to control for the issue size effect) and bond coupon into the pricing equation.

We follow the same methodology as in Section 2.4, where credit rating is converted into the numerical representation by the same way as described in Figure 2-3.[41] We have done the analysis using both a single cross-sectional regression and Fama-MacBeth (with 5-year rolling betas) method. Since both give similar results, we report only the results from the first method to save space. In Table 2-8, when liquidity risks are included in the cross-sectional regression, the impacts of credit ratings and bond duration on expected bond returns are weak and insignificant. Only in model 8.1, where the market risk factor alone is entered into the pricing equation, are credit ratings positive and marginally insignificant, suggesting that credit rating and/or duration may partly represent unknown risks (possibly liquidity risk). Intuitively, we expect the coefficients in front of both $E(CR^i_t)$ and $E(MD^i_t)$ to be positive since they represent default and term risk respectively.[42] In our results, $E(CR^i_t)$ is correctly positive in all specifications, although it is not significant in all specifications. Investors expect higher returns from holding higher default-risk securities. Even though $E(MD^i_t)$ is not significant in any specification, it is always negative, which is not as expected. A reason behind this might be the endogeneity problem: a low-cost-of-borrowing country may prefer to lock in its cost of capital by issuing longer-term bonds. A high-cost-of-borrowing country usually with bad credit rating may not be able to sell its long-term bonds at a reasonable price and may be forced to issue shorter-term instruments.

To summarize, the evidence indicates that liquidity risk and liquidity level are priced in the international bond markets even in the presence of individual bond portfolios' credit

[41] The average credit rating during January 2000 to August 2008 is about 11.56 (around BB to BB+). The highest credit rating in our sample is A+.

[42] If there is no default risk and interest rate term risk, we should expect the credit rating and modified duration to be zero and insignificant because in constructing our expected excess returns in Section 2.4.5, we adjust them for default loss and term structure of interest.

quality and maturity. Our results are in line with those reported by Gebhardt et al. (2005). They find that bond characteristics such as credit rating and duration are less important than systematic risk factors as far as U.S. corporate bond returns are concerned.

Table 2-8: Country portfolios and cross-sectional regression with credit rating and modified duration

This table reports results from the cross-sectional regression of the unconditional LCAPM in Equation (2.7) for 42 value-weighted country portfolios using weekly data during January 1995 to July 2008 with a value-weighted market portfolio. Specifications, which are considered, are alternative cases of the following equation:

$$E(r_t^i - r_t^f)^* = \alpha + \omega E(c_t^i) + \lambda^1\beta^{1,i} + \lambda^2\beta^{2,i} + \lambda^3\beta^{3,i} + \lambda^4\beta^{4,i} + \lambda^5\beta^{NET,i} + \lambda^6\beta^{LIQ,i} + \gamma E(CR_t^i) + \kappa E(MD_t^i),$$

where $E(r^i_t - r^f_t)^*$ is the average expected excess return for country *i*. $E(c^i_t)$ is the average quoted bid/ask spread. $\beta^{1,i}$ is the market beta, $\beta^{2,i}$, $\beta^{3,i}$ and $\beta^{4,i}$ represent three liquidity betas. $\beta^{NET,i} = \beta^{1,i} + \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$ and $\beta^{LIQ,i} = \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$. Betas are pre-estimated using Equation (2.5). In some specification, ω is set to be the average weekly turnover (ω = 0.04 or annual turnover of about two). $E(CR^i_t)$ is the average Standard & Poor's long-term and foreign currency debt credit rating for country *i*. $E(MD^i_t)$ is the average modified duration of eligible bonds for country *i.* The t-statistics from Newey and West (1987) heteroskedasticity-consistent standard error & covariance least square regression are in the parentheses. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively. To save spaces, the R^2 (and adjusted R^2) is not reported here.

	constant (α)	$E(c^i_t)$	$\beta^{1,i}$ Cov(r^i,r^M)	$\beta^{2,i}$ Cov(c^i,c^M)	$\beta^{3,i}$ Cov(r^i,c^M)	$\beta^{4,i}$ Cov(c^i,r^M)	$\beta^{NET,i}$ Sum of 4 betas	$\beta^{LIQ,i}$ Liquidity Beta sum	$E(CR^i_t)$	$E(MD^i_t)$
8.1	-0.0163		0.0012[c]						0.0040	-0.0018
	-(0.56)		(5.09)						(1.55)	-(0.83)
8.2	-0.0221	0.0400					0.0012[c]		0.0004	-0.0012
	-(0.65)	(-)					(5.49)		(0.13)	-(0.47)
8.3	-0.0208	0.0248[b]					0.0012[c]		0.0018	-0.0014
	-(0.65)	(2.30)					(5.65)		(0.62)	-(0.63)
8.4	-0.0104	0.0400	0.0025[c]	0.0933	0.0364	0.0075			0.0001	-0.0024
	-(0.39)	(-)	(3.22)	(1.12)	(1.61)	(1.47)			(0.02)	-(0.89)
8.5	-0.0126	0.0316[b]	0.0022[b]	0.1086	0.0303	0.0076			0.0009	-0.0022
	-(0.49)	(2.47)	(2.40)	(1.09)	(1.21)	(1.45)			(0.36)	-(0.91)
8.6	-0.0309	0.0400						0.0073[c]	0.0022	-0.0007
	-(0.66)	(-)						(2.74)	(0.56)	-(0.16)
8.7	-0.0315	0.0071						0.0082[c]	0.0050	-0.0008
	-(0.79)	(0.54)						(3.31)	(1.26)	-(0.27)

2.6.2 Does U.S. stock market drive emerging sovereign bond markets?

It is interesting to test whether the U.S. stock market is a driving force of global liquidity risks. This section therefore investigates the pricing effect of the comovements of country bond portfolio returns and illiquidity with those of the U.S. stock market. In building an econometric model, we decompose global market returns, r^G_t, and illiquidity, c^G_t, into those of total emerging U.S. dollar sovereign bond market and the U.S. stock market as follows:

$$r_t^G = \alpha \cdot r_t^M + (1-\alpha)\cdot r_t^{US},$$
$$c_t^G = \alpha \cdot c_t^M + (1-\alpha)\cdot c_t^{US}, \qquad (2.13)$$

where $r^M{}_t$ ($c^M{}_t$) is return (illiquidity cost) on global emerging bond market (i.e., EMBI) and $r^{US}{}_t$ ($c^{US}{}_t$) is return (illiquidity cost) from U.S. stock market. α is fraction of the market value of EMBI to the global market.

Combining Equation (2.1) with Equation (2.13), the liquidity-adjusted CAPM can be extended to

$$E_t(r_{t+1}^i - c_{t+1}^i)^* = r_t^f + \lambda_t \frac{\mathrm{cov}_t(r_{t+1}^i - c_{t+1}^i, \left[\alpha \cdot r_t^M + (1-\alpha)\cdot r_t^{US}\right] - \left[\alpha \cdot c_t^M + (1-\alpha)\cdot c_t^{US}\right])}{\mathrm{var}_t(r_{t+1}^G - c_{t+1}^G)}. \qquad (2.14)$$

Therefore, the unconditional version will be[43]

$$E(r_t^i - r_t^f)^* = E(c_t^i) + \lambda_1^M \beta^{1i,M} + \lambda_2^M \beta^{2i,M} - \lambda_3^M \beta^{3i,M} - \lambda_4^M \beta^{4i,M}$$
$$+\lambda_1^{US} \beta^{1i,US} + \lambda_2^{US} \beta^{2i,US} - \lambda_3^{US} \beta^{3i,US} - \lambda_4^{US} \beta^{4i,US}, \qquad (2.15)$$

where

$$\beta^{1i,M} = \frac{\mathrm{cov}(r_t^i, r_t^M - E_{t-1}(r_t^M))}{\mathrm{var}(r_t^G - E_{t-1}(r_t^G) - [c_t^G - E_{t-1}(c_t^G)])},$$

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[43] Lee (2010) uses a similar methodology in studying the global liquidity risk and ex post returns using data from individual stocks from 48 countries. However, we use bond data, which enable us to obtain more accurate measure of expected returns.

$$\beta^{2i,M} = \frac{\text{cov}(c_t^i - E_{t-1}(c_t^i), c_t^M - E_{t-1}(c_t^M))}{\text{var}(r_t^G - E_{t-1}(r_t^G) - [c_t^G - E_{t-1}(c_t^G)])},$$

$$\beta^{3i,M} = \frac{\text{cov}(r_t^i, c_t^M - E_{t-1}(c_t^M))}{\text{var}(r_t^G - E_{t-1}(r_t^G) - [c_t^G - E_{t-1}(c_t^G)])},$$

$$\beta^{4i,M} = \frac{\text{cov}(c_t^i - E_{t-1}(c_t^M), r_t^M - E_{t-1}(r_t^M))}{\text{var}(r_t^G - E_{t-1}(r_t^G) - [c_t^G - E_{t-1}(c_t^G)])},$$

$$\beta^{1i,US} = \frac{\text{cov}(r_t^i, r_t^{US} - E_{t-1}(r_t^{US}))}{\text{var}(r_t^G - E_{t-1}(r_t^G) - [c_t^G - E_{t-1}(c_t^G)])},$$

$$\beta^{2i,US} = \frac{\text{cov}(c_t^i - E_{t-1}(c_t^i), c_t^{US_i} - E_{t-1}(c_t^{US}))}{\text{var}(r_t^G - E_{t-1}(r_t^G) - [c_t^G - E_{t-1}(c_t^G)])},$$

$$\beta^{3i,US} = \frac{\text{cov}(r_t^i, c_t^{US} - E_{t-1}(c_t^{US}))}{\text{var}(r_t^G - E_{t-1}(r_t^G) - [c_t^G - E_{t-1}(c_t^G)])},$$

$$\beta^{4i,US} = \frac{\text{cov}(c_t^i - E_{t-1}(c_t^i), r_t^{US} - E_{t-1}(r_t^{US}))}{\text{var}(r_t^G - E_{t-1}(r_t^G) - [c_t^G - E_{t-1}(c_t^G)])}.$$

Therefore, we can now jointly test the effects of liquidity risks resulting from the global emerging U.S. dollar bond market and the U.S. stock market dimensions. The weight, α, in Equation (2.13) is forced to be included in the estimated premia of λ^M and λ^{US} in the regression. All betas in Equation (2.16) have a common denominator of variances related to the total return and illiquidity cost of EMBI and U.S. stock market. If we assume that $\lambda^G = \lambda^M = \lambda^{US}$, Equation (2.15) can be rewritten in term of the net beta as follows:

$$E(r_t^i - r_t^f)^* = E(c_t^i) + \lambda^G \beta^{NET,i,G} \text{ or}$$
$$E(r_t^i - r_t^f)^* = E(c_t^i) + \lambda^M \beta^{NET,i,M} + \lambda^{US} \beta^{NET,i,US}, \qquad (2.16)$$

where

$$\beta^{NET,i,G} = \beta^{NET,i,M} + \beta^{NET,i,US}$$
$$= \left[\beta^{1,i,M} + \beta^{2,i,M} - \beta^{3,i,M} - \beta^{4,i,M}\right] + \left[\beta^{1,i,US} + \beta^{2,i,US} - \beta^{3,i,US} - \beta^{4,i,US}\right]. \qquad (2.17)$$

Equation (2.16) is our unconditional LCAPM, incorporating risk factors both from emerging bond and U.S. stock markets. In the extreme case of fully-segmented emerging U.S. dollar bond markets and the U.S. stock market, we expect λ^{US} to be equal to zero.

2.6.2.1 U.S. stock market data

For the U.S. stock market, we use monthly returns from the Center for Research in Security Prices (CRSP), which includes all common shares listed on NYSE and AMEX, from January 1995 to December 2006. Our sample period is reduced because we employ the monthly measure of innovation in illiquidity calculated by Pastor and Stambaugh (2003), which are available from Wharton Research Data Service website until December 2006.[44] Their innovations in U.S. stock market illiquidity are estimated from the same CRSP data as the stock market returns. We derive the bond data as before, but with the corresponding monthly interval.

2.6.2.2 Results from cross-section liquidity-adjusted CAPM regression

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[44] In their paper, they measure liquidity. In order to obtain the measure of illiquidity, we simply switch their signs (i.e., from positive to negative and vice versa).

After decomposing global market factors (superscript "*G*") into those of the bond market (superscript "*M*") and the U.S. stock market (superscript "*US*") in Equations (2.16) and (2.17), Table 2-9 reports the pricing effect of the comovements of bond returns with bond and U.S. stock factors. Model 9.1 shows that the risk premium of global net beta, $\beta^{NET,G}$, and the coefficient of expected illiquidity cost, $E(c^i_t)$, are highly significant and positive (as expected), while the pricing error or constant is not significant. However, when the bond net beta and the U.S. stock net beta are separately included in model 9.2, the risk factors in the bond market outshine those in the U.S. stock market. Understandably, this is because our test assets are bonds. Again, if we allow all of the betas to have different risk premia, λ^i, in models 9.5, 9.6 and 9.7 because of the multicollinearity problem in betas (see Table 2-3), the evidence of liquidity risk is weak. Nevertheless, those three specifications suggest that market risk relating to the U.S. stock market, $\beta^{1,US}$, has some influence over the excess bond returns, whereas effects of liquidity risks resulting from the U.S. stock market illiquidity are relatively weak. The last statement is confirmed by regression results in model 9.10, where the sum of liquidity betas relating to the U.S. stock market illiquidity or $\beta^{LIQ,US}$ is not significant.

Overall, our findings are consistent with previous results reported by Min, Lee, Nam, Park and Nam (2003), Diaz-Weigel and Gemmill (2006) and Longstaff et al. (2005) that the credit spreads in the emerging markets reflect the global and/or regional factors such as the U.S. stock market. Both bond and stock are subject to a common market factor or to some extent they share the same pricing kernel, which prices all risky assets. This also suggests that our bond-liquidity risk premium is not sensitive to the choice of market risk factors. However, the evidence of a liquidity spillover (or flight-to-liquidity

Table 2-9 Country bond portfolios and cross-sectional regression with both bond and U.S. stock market risk factors

This table reports results from the cross-sectional regression of the unconditional LCAPM in Equation (2.16) for 42 value-weighted country portfolios using monthly data during January 1995 to December 2006 with a value-weighted market portfolio. Specifications, which are considered, are alternative cases of the following equation:

$$E(r_t^i - r_t^f)^* = \alpha + \omega E(c_t^i) + \lambda_1^1 \beta^{1i,M} + \lambda^2 \beta^{2i,M} - \lambda^3 \beta^{3i,M} - \lambda^4 \beta^{4i,M} + \lambda^5 \beta_6^{1i,US} + \lambda^6 \beta^{2i,US} - \lambda^7 \beta^{3i,US} - \lambda^8 \beta^{4i,US}$$
$$+\lambda^9 \beta^{NET,i,G} + \lambda^{10} \beta^{LIQ,i,G} + \lambda^{11} \beta^{NET,i,M} + \lambda^{12} \beta^{LIQ,i,M} + \lambda^{13} \beta^{NET,i,US} + \lambda^{14} \beta^{LIQ,i,US},$$

where $E(r^i_t - r^f_t)^*$ is the average expected excess return for country *i*. $E(c^i_t)$ is the average quoted bid/ask spread. $\beta^{1,i}$ is the market beta, $\beta^{2,i}$, $\beta^{3,i}$ and $\beta^{4,i}$ represent three liquidity betas. $\beta^{NET,i} = \beta^{1,i} + \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$ and $\beta^{LIQ,i} = \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$. *G*, *M* and *US* denote global (*M+US*), emerging sovereign U.S. dollar bond market and U.S. stock market respectively. Betas are pre-estimated using Equation (2.15). The t-statistics from Newey and West (1987) heteroskedasticity-consistent standard error & covariance least square regression are in the parentheses. Significance at the 10%, 5% and 1% level is indicated by [a], [b] and [c] respectively. To save spaces, the R^2 (and adjusted R^2) is not reported here.

	constant (α)	$E(c^i_t)$	$\beta^{1,i,M}$	$\beta^{2,i,M}$	$\beta^{3,i,M}$	$\beta^{4,i,M}$	$\beta^{1,i,US}$	$\beta^{2,i,US}$	$\beta^{3,i,US}$	$\beta^{4,i,US}$	$\beta^{NET,i,G}$	$\beta^{NET,i,M}$	$\beta^{NET,i,US}$	$\beta^{LIQ,i,G}$	$\beta^{LIQ,i,M}$	$\beta^{LIQ,i,US}$
			Cov(r^i,r^M)	Cov(c^i,c^M)	Cov(r^i,c^M)	Cov(c^i,r^M)	Cov(r^i,r^{US})	Cov(c^i,r^{US})	Cov(r^i,c^{US})	Cov(c^i,r^{US})	Sum of 8 betas	Sum of 4 bond betas	Sum of 4 stock betas	Liquidity beta sum	Liquidity beta sum (bond)	Liquidity beta sum (stock)
9.1	-0.0147	0.0393[b]									0.1061[c]					
	-(1.08)	(2.56)									(7.78)					
9.2	-0.0298	0.0488[c]										0.3843[b]	-0.3839			
	-(1.77)	(2.91)										(2.17)	-(1.37)			
9.3	-0.0191	0.0407[c]										0.1743[c]				
	-(1.47)	(2.87)										(6.38)				
9.4	-0.0070	0.0385[b]											0.2506[c]			
	-(0.46)	(2.24)											(5.82)			
9.5	-0.0469	0.0447[c]	1.0951[a]	332.3598	27.0433	7.1311	-1.0720[a]	-24.4026	8.5724	-17.6392						
	-(1.70)	(2.92)	(1.76)	(1.53)	(1.19)	(1.23)	-(1.73)	-(0.04)	(0.65)	-(1.60)						
9.6	-0.0231	0.0475[b]	0.1389	428.9741	-1.9713	0.6221										
	-(1.29)	(2.17)	(0.70)	(1.53)	-(0.12)	(0.34)										
9.7	-0.0103	0.0367[a]					0.2525[a]	637.9001	5.5199	1.7472						
	-(0.50)	(1.82)					(1.79)	(0.88)	(0.24)	(0.48)						
9.8	0.0043	0.0336[a]												2.6460[b]		
	(0.39)	(1.72)												(2.72)		
9.9	0.0009	0.0345[a]													3.7709[c]	
	(0.09)	(1.88)													(3.15)	
9.10	0.0072	0.0481[b]														2.6720
	(0.57)	(2.40)														(0.80)

effect) from the U.S. stock market to emerging U.S. dollar bond markets is statistically weak. This is despite Sarkar and Subrahmanyam (2005) showing that liquidity in U.S. stock and Treasury bond markets is correlated. Further studies on these joint effects may yield interesting results.

2.6.3 Out-of-sample analysis: August 2008 to February 2009

With the same methodology as in Section 2.4, we confirm our previous results with out-of-sample data from September 2008 to February 2009 (i.e., during global credit crunch period), i.e., we use in-the-sample betas from Section 2.5.1 to forecast out-of-sample expected excess bond returns. Table 2-10 shows that liquidity is still an important driving force in determining the expected excess bond return during this out-of-sample period. In general, results are very similar to those in Section 2.5.1. However, there is a meaningful difference in that the CAPM now has no explanatory power for the expected excess bond returns (model 10.1). In fact, the market beta, $\beta^{1,i}$, is not significant in any specification, even though it is positively priced in models 10.1, 10.4 and 10.5. Liquidity betas maintain their significance and have a stronger economic effect in this out-of-sample period. Models 10.2 and 10.3 support our LCAPM. Again, comparing models 10.1 with 10.2, the adjusted R^2 is a lot higher when liquidity risks are included in the pricing equation and the number of the free parameters is the same.

During this out-of-sample period, the evidence of liquidity risk is stronger than before, even though all of the betas are allowed to have different risk premium, λ^i, in models 10.4 and 10.5. Those two specifications again provide evidence that liquidity risk is important over and above the market risk during this period. Especially in model 10.4, where the holding period is fixed, liquidity betas are all significant and signed as expected. Respectively, Panels A, B and C in Figure 2-5 show the empirical fit of the standard CAPM from model 10.1 in Table 2-10, constrained LCAPM from model 10.2 in Table 2-10 and unconstrained LCAPM from model 10.5 in Table 2-10. Liquidity risks significantly improve fit and the improvement does not result from the increase in the degree of freedom.

Table 2-10: Country portfolios and cross-sectional regression with out-of-sample excess bond returns

This table reports results from the cross-sectional regression of the unconditional LCAPM in Equation (2.7)) for 42 value-weighted country portfolios using weekly data during September 2008 to February 2009 with a value-weighted market portfolio. Specifications, which are considered, are alternative cases of the following equation:

$$E(r_t^i - r_t^f)^* = \alpha + \omega E(c_t^i) + \lambda^1 \beta^{1,i} + \lambda^2 \beta^{2,i} + \lambda^3 \beta^{3,i} + \lambda^4 \beta^{4,i} + \lambda^5 \beta^{NET,i} + \lambda^6 \beta^{LIQ,i},$$

where $E(r^i_t - r^f_t)^*$ is the average expected excess return for country *i*. $E(c^i_t)$ is the average quoted bid/ask spread. $\beta^{1,i}$ is the market beta, $\beta^{2,i}$, $\beta^{3,i}$ and $\beta^{4,i}$ represent three liquidity betas. $\beta^{NET,i} = \beta^{1,i} + \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$ and $\beta^{LIQ,i} = \beta^{2,i} - \beta^{3,i} - \beta^{4,i}$. Betas are pre-estimated using Equation (2.5). In some specification, ω is set to be the average weekly turnover ($\omega = 0.04$ or annual turnover of about two). The t-statistics from Newey and West (1987) heteroskedasticity-consistent standard error & covariance least square regression are in the parentheses. R^2 and Adjusted R^2 are reported in the last column. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively.

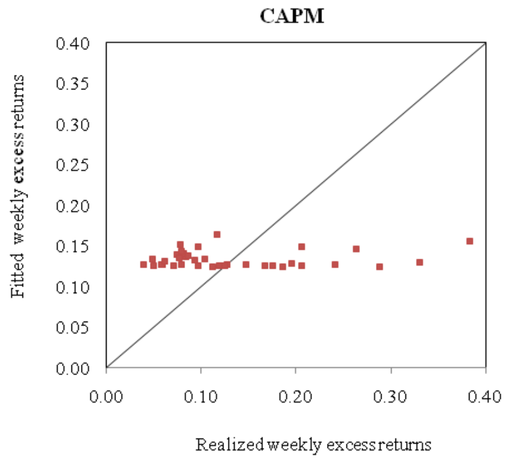
	constant (α)	$E(c^i_t)$	$\beta^{1,i}$ Cov(r^i,r^M)	$\beta^{2,i}$ Cov(c^i,c^M)	$\beta^{3,i}$ Cov(r^i,c^M)	$\beta^{4,i}$ Cov(c^i,r^M)	$\beta^{NET,i}$ Sum of 4 betas	$\beta^{LIQ,i}$ Liquidity Beta sum	R^2 (adj-R^2)
10.1	0.1183[c]		0.0489						0.03
	(8.21)		(1.24)						(0.00)
10.2	-0.0377[b]	0.0400					0.1228[b]		0.18
	-(2.14)	(-)					(2.51)		(0.16)
10.3	0.0379[c]	0.0208[c]					0.0859[b]		0.37
	(3.81)	(7.09)					(2.17)		(0.30)
10.4	-0.0380	0.0400	0.0190	18.7854[c]	-6.1139[c]	-1.1358[a]			0.51
	-(1.56)	(-)	(0.42)	(3.74)	-(3.02)	-(1.95)			(0.45)
10.5	-0.0063	0.0167[c]	0.0099	1.2432	-7.6866[c]	-0.7420[a]			0.65
	-(0.52)	(5.14)	(0.32)	(0.20)	-(5.04)	-(2.12)			(0.59)
10.6	0.0288	0.0400						1.6516[c]	0.29
	(1.58)	(-)						(3.10)	(0.27)
10.7	0.0697[c]	0.0244[c]						1.0030[a]	0.33
	(4.56)	(3.40)						(1.73)	(0.29)

In conclusion, the results are still very supportive of the hypothesis that liquidity is priced in the international bond market or the cross-sectional difference in liquidity can explain the differences in average returns in the international bond market during the out-of-sample period. However, the market risk has lost its power in explaining the out-of-sample excess bond returns. It follows that the liquidity impact could be time-varying and increases during periods of crisis. We will investigate this issue more closely in the next chapter.

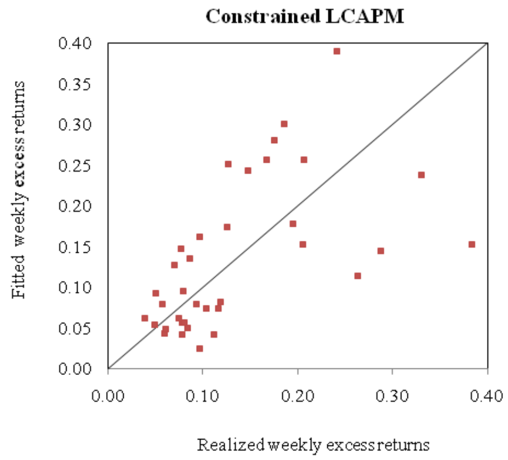
Figure 2-5: Out-of-sample empirical fit of CAPM versus LCAPM

Panel A depicts the fitted CAPM returns against realized returns using weekly data from September 2008 to February 2009 for value-weighted country portfolios. Panel B shows the same for the constrained LCAPM and Panel C represents the same for the unconstrained LCAPM.

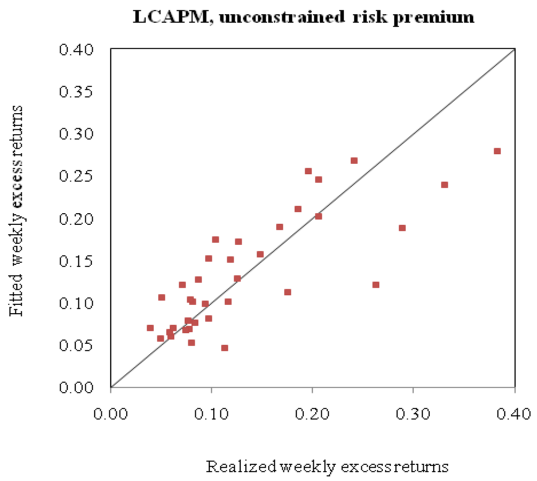
Panel A



Panel B



Panel C



2.7 Conclusions

Our results show that liquidity level and liquidity risks are priced in the emerging U.S. dollar sovereign bond markets. Compared to the standard CAPM with the same degrees of freedom, liquidity risks from the LCAPM improve fit for both low yield and high yield sovereign-bond portfolios. Country bond portfolios, which have higher market beta, higher liquidity betas and higher quoted bid/ask spreads, tend to have greater expected excess returns after adjusting for default loss. Surprisingly more illiquid portfolios (higher quoted bid/ask spreads) do not always have a higher level of liquidity risk (higher liquidity betas). Provided that the LCAPM is correctly specified, the combined effects of liquidity risk and liquidity level can account for 100 basis points of yield spread difference between the highest and lowest liquidity risk countries in the sample, which are Croatia and Ghana respectively. Even though Ghana has a lower credit rating and issues longer-term bonds than Croatia, it has a lower bond yield spread. This evidence supports a flight to liquidity effect across our sample and is still robust when we include the portfolios' characteristics in our model. In addition, liquidity betas are able to maintain their significance and have a stronger economic effect in an out-of-sample period, while the market risk has lost its power in explaining bond expected returns.

Our evidence also suggests that the U.S. stock market risk is a driving force in determining the average excess bond returns. Countries with a high correlation with the global market or U.S. stock market have higher expected bond returns than low correlation countries. When the U.S. stock market goes down, international investors would like to rebalance their portfolios. Bonds are less desirable if their prices decline when the U.S. stock market plummets. Therefore, investors require higher returns when holding securities that have less diversification benefits. However, the impact of liquidity risk in the U.S. stock market on bond returns is not as statistically strong.

So far, the analysis on the effect of liquidity on the cross-sectional asset pricing has been unconditional by nature. Although we find clear evidence that a bond's comovement with market factors are priced, the significance of both market and liquidity risks in explaining excess returns seems to be time-varying when we compare the results in in-sample and out-of-sample analyses. Further investigation on time-varying liquidity betas and liquidity risk premium could be beneficial. The next chapter features the study on a conditional version of the asset pricing model for the international bond market.

CHAPTER 3

PRICING OF GOVERNMENT BONDS AROUND THE WORLD AND TIME-VARYING LIQUIDITY RISK

Abstract

This paper finds that both liquidity level and liquidity risk are important in explaining the cross-section of domestic government bond returns in 39 countries (both emerging and developed) around the world. After controlling for other market factors and bond characteristics, liquidity level and liquidity risk together can explain as much as 0.41% per annum of extra yield for the highest versus the lowest liquidity risk countries, which are China and Argentina respectively. There is also an evidence of liquidity spillovers from the U.S. equity market to domestic bond markets around the world. Employing a conditional model, which allows both time-series and cross-sectional variations in liquidity betas, we find that the impact of liquidity risk is time varying across two different regimes: it increases in times of high uncertainty and is always larger in emerging than in developed countries. Nevertheless, the price of risk or premium required by investors for holding this time-varying risk is relatively modest.

3.1 Introduction

The fact that liquidity varies over time is well known (e.g., Chordia, Roll and Subrahmanyam (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001), Amihud (2002), Pastor and Stambaugh (2003), Korajczyk and Sadka (2008)). We have witnessed very significant liquidity shocks at particular times (for example, 1987- U.S. stock market crash, 1997- Asian Crisis, 1998- Russia and LTCM crises and 2008-credit crunch). Such liquidity shocks can be transmitted from one country to another extremely fast. However, the analysis of most previous papers on the effect of liquidity on the cross-section of asset prices has been unconditional in nature and concentrated on U.S. market.

In this paper, we investigate the relationships between local-currency bond returns and liquidity factors around the world incorporating 12 emerging countries and 27 developed countries. Global risk factors are therefore taken into consideration. The data span more than 20 years, from December 1985 to February 2009. In the unconditional setting, we follow the framework of Pastor and Stambaugh (2003) and De Jong and Driessen (2006) and use a two-step Fama-MacBeth (1973) procedure. We find that the global liquidity risk is priced in local-currency government bond markets around the world after controlling for bond characteristics and relevant risk factors. In the conditional setting, where we allow not only for time-series, but also for cross-sectional variations in liquidity betas, a regime-switching model is used as pioneered for liquidity risk by Watanabe and Watanabe (2008) on U.S. equities and Acharya, Amihud and Bharath (2010) on U.S. corporate bonds. The former paper finds that for U.S. stocks, the pricing of liquidity risk becomes stronger in the high liquidity-beta state. The latter investigates liquidity risk of U.S. corporate bond returns, focusing on the conditional effects during the bad state (high liquidity-beta state) and the difference between high-rated and low-rated bonds. For low-rated U.S. corporate bonds, it finds that the effects of liquidity risk are significantly greater during periods of stress.

This is the first paper to study the effects of liquidity risk and its time-variation on bond prices in a comprehensive set of both developed and emerging countries. Bonds provide a relatively good environment in which to test asset pricing models because the expected (forward-looking) return on a bond can be constructed with some precision.[45] Using a regime-switching model, we find that the transition from the low to the high liquidity-beta states (i.e., from states in which liquidity does not matter to states in which it does) can be predicted from a decline in U.S. equity market performance and from a rise in bond market volatility. This is consistent with results for U.S. equity markets: Watanabe and Watanabe (2008) report that the high-beta state for U.S. equities is associated with high equity volatility and preceded by a period of declining expectations about future market liquidity. We also investigate whether there is a time-varying risk-premium for liquidity and find that the economic significance of time-varying liquidity risk on the credit spread is about half that of unconditional liquidity risk.

The importance of liquidity risk for asset prices is recognized by both academics and practitioners, so a well-specified dynamic model with liquidity risk is an essential step towards a more realistic pricing model for bonds. Our paper is a contribution to such a model, although, as yet, we can only explain part of the observed time variation in liquidity.

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[45] This contrasts with using stocks for which the long-term historical (backward-looking) average return is often used as a proxy for the expected return.

In addition, our paper offers a new set of data to the literature, i.e., local-currency government bonds, which are issued under a country's own legal jurisdiction. Domestic bonds have been by default disregarded by researchers, who always focus on sovereign debts or international bonds. However, the domestic debts constitute almost two-thirds of total public debts in 64 countries during 1900– 2007 and are the main source of country's defaults and financial turbulences (Reinhart and Rogoff (2009)). We use the bid/ask spread as a direct measure of liquidity, where their series have not been compiled before.

The remainder of the paper is organized as follows. Section 3.2 presents the related literature. Section 3.3 describes the data used. The methodology and empirical results for unconditional liquidity risk are reported in the Section 3.4. Those for conditional liquidity risk are given in Section 3.5. Section 3.6 concludes the paper.

3.2 Related Literature

The difference between yields on risky and risk-free bonds of equivalent maturity, known as the credit spread, appears to be "too high". It is inconsistent with observed default and recovery rates and with most models of credit risk (both structural models and reduced-form models).[46] Collin-Dufresne, Goldstein and Marting (2001) find that changes in spreads cannot be explained by changes in factors affecting credit risk and that the unexplained portion appears to be driven by a common factor. Recent work by Schaefer and Strebulaev (2008) supports their argument that the unexplained portion is likely to be independent from credit risk. Liquidity, liquidity risk and a time-varying risk premium are among a set of possible explanations.

Studies of liquidity and asset pricing have been pioneered in a cross-sectional framework. The first among them is the paper by Amihud and Mendelson (1986), who report a positive cross-sectional relationship between equity returns and illiquidity. Since then, there have been many cross-sectional studies on liquidity and asset pricing, for example, Brennan and Subrahmanyam (1996), Chordia, Roll and Subrahmanyam (2000) and Chordia, Subrahmanyam and Anshuman (2001). The last study finds a negative cross-sectional relationship between stock returns and trading activity as a proxy for liquidity and between returns and the volatility of trading activity as a proxy for liquidity risk after controlling for size, book-to-market, momentum, dividend yield and price level. These findings suggest that investors are averse to the variability of liquidity, i.e., to liquidity risk.

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[46] Eom, Helwege and Huang (2004) provide good empirical evidence on various structural models. For reduced-form models, see for example, Duffie and Singleton (1999) and Jarrow, Lando and Turnbull (1997).

As already noted, following Amihud and Mendelson (1986), there have been several empirical studies, which emphasize the importance of liquidity in static models (for example, Eleswarapu and Reinganum (1993), Brennan, Chordia and Subrahmanyam (1998), Chalmers and Kadlec (1998), Datar, Naik and Radcliffe (1998), Chordia, Subrahmanyam and Anshuman (2001), Chordia, Roll and Subrahmanyam (2002), Pastor and Stambaugh (2003) and Acharya and Pedersen (2005)). The latter two papers focus on the significance of the price of liquidity risk, where stocks with higher liquidity betas should be compensated with higher expected returns. Lee (2010) extends the Acharya and Pedersen's liquidity-adjusted CAPM to the international stock markets. Amihud (2002) introduces new tests, which distinguish between an increase in expected illiquidity, which positively affects ex ante stock returns and an increase in unexpected illiquidity, which has a negative effect on contemporaneous stock returns. Besides the novelty in testing the liquidity-return relationship over time, he also introduces a new measure of liquidity based on daily returns and volume data.[47] Using a similar approach to Amihud (2002), Gibson and Mougeot (2004) define a liquidity proxy, which is the standardized number of shares traded in the S&P 500 index during a month.[48] Using this measure, they find that the liquidity premium of the S&P 500 index return is time-varying and related to the probability of a future recession.

Despite all of the above results, the role of liquidity in time-varying models has not been adequately addressed both because of the potential omission of variables and because data are not available for the accurate measurement of liquidity. There has been

[47] His measure is calculated as the absolute change in return per dollar volume. The higher this measure, the lower security's liquidity.

[48] Gibson and Mougoet (2004)'s measure of liquidity should be negatively related to Amihud's.

very little attempt to investigate how pricing models with liquidity dynamics might change over time. One exception is Watanabe and Watanabe (2008), who begin to study the dynamics of liquidity for stocks across two different economic states: high and low liquidity-beta states. Transition from the low to the high liquidity-beta state is predicted by a rise in trading volume, which is a proxy for greater preference uncertainty. Not only is liquidity risk or liquidity beta found to be contingent on the state of the world, but the liquidity risk premium is found to be economically more important in the high liquidity-beta state. Their findings imply that liquidity is closely linked with trading volume and perhaps with volatility.

There is a paucity of studies about how liquidity dynamics could affect bond pricing and none has been done in the context of international bond markets. Works on liquidity and bond pricing start with Amihud and Mendelson (1991). They find differences in yields between U.S. Treasury bills and U.S. Treasury notes with the same maturity. As these two securities are completely identical, the yield spreads between them must be accounted for a difference in liquidity as measured by the bid/ask spread and broker fees.[49] Moreover, the price impact on bills is smaller than on notes, meaning that a bill can trade in larger amounts without affecting its prevailing market price. Similarly, Kamara (1994) reports that note and bill spread differences hold after controlling for a number of security characteristics. Warga (1992) and Krishnamurthy (2002) find a similar pattern in the yield difference between U.S. on-the-run (most recent auctioned) and off-the-run government bonds: around 0.55% per annum yield difference is

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[49] U.S. Treasury bills are much more liquid than notes.

estimated by Warga (1992).[50] Longstaff (2004) investigates the dynamic nature of the liquidity risk premium in U.S. Treasury bond prices and reports that there is a large illiquidity premium, which is highly correlated with market sentiment measures such as changes in the Conference Board Consumer Confidence Index and in the amount of capital held in money-market mutual funds. However, he does not study how liquidity dynamics affect the cross-section of U.S. Treasury bond returns. Using data on the Euro-area government bond market, Beber, Brandt and Kavajecz (2009) find that yield spreads can be explained by differences in liquidity especially for low credit risk countries and during times of heightened market uncertainty. We conjecture that it is a result of conditional or time-varying effects of liquidity.

Several empirical studies support an effect of liquidity level on U.S. corporate bonds' prices including Perraudin and Taylor (2003), Howeling, Mentink and Vorst. (2005), Chacko (2006), Chen, Lesmond and Wei (2007) and Goldstein, Hotchkiss and Sirri (2007). In general, they suggest that a significant portion of the yield spread between corporate and government bonds is due to illiquidity costs. Although most works are in the cross-sectional framework, Chen, Lesmond and Wei (2007) conduct a time-series analysis and report that changes in illiquidity induce changes in yields in the same direction. The price of liquidity risk in the U.S. corporate bond market is investigated by De Jong and Driessen (2006) and Jacoby, Theocharides and Zheng (2007). Both papers rely on an unconditional analysis and have relatively limited data in time-series. Acharya, Amihud and Bharath (2010) start to examine the unconditional and conditional sensitivity of monthly U.S. corporate bond returns to liquidity factors over

[50] See Elton and Green (1998), Chakravarty and Sircar (1999), Fleming (2002), Downing and Zhang (2004) and Longstaff (2004) for studies, which find that liquidity, as a bond characteristic, helps explain the government bond yield difference.

1973 to 2003. They find that liquidity risk, either from U.S. Treasury bonds or from the stock market, significantly affects returns on sub-investment grade bond, while little evidence is found for an effect on investment grade bond returns. Liquidity betas of sub-investment grade bonds occasionally switch to a regime with extremely high values. Their analysis is confined to changes in time-series liquidity betas and does not extend to changes in the price of risk; the important question of how time-varying liquidity risk affects the cross-section of expected returns is therefore not investigated.

So far, the study of liquidity in bond markets has been limited to U.S. markets and no paper has studied the impact of liquidity risk on the expected returns of government bonds in an international setting. Therefore, we focus our attention in this paper on internationally-traded local-currency government bonds, where the data on bid/ask spreads can be collected for a long period. Our paper fills a gap in the existing literature by examining both unconditional and conditional international bond pricing models and allowing for both time-series and cross-sectional variations in liquidity risks.

3.3 Data and Summary Statistics

Our test assets are the local-currency government bonds, which are included in the JPMorgan Government Bond Index (GBI) and the JPMorgan Government Bond Index-Emerging Market (EM). These bonds are regularly traded, fixed-rate, domestic government bonds of countries that offer opportunities to international investors.[51] To be included, countries must have: relatively liquid and stable government debt markets; active trading in good volumes; regular issuance; and easy access for foreign investors.[52] International investors would consider such bonds for inclusion in their global bond market portfolios.

Available metrics for bonds included in the indices are the bond's clean price, coupon, accrued interest, yield to maturity, modified duration, remaining maturity and bond market value outstanding. Data on each individual bond's bid and ask prices are collected from Bloomberg. These are not matrix prices, but actual quotes from bond traders. It should be noted that these bonds are denominated in domestic currencies (not U.S. dollar, except for U.S. bonds). The U.S. dollar foreign exchange rates are also downloaded from the JPMorgan system.

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[51] The universe of bonds excludes floating rate notes, perpetual bonds, bonds with less than one year to maturity, bonds targeted at the domestic market for tax reasons and bonds with callable, puttable or convertible features.

[52] There is no universal standard of liquidity application to the international government bond market. However, the indices include only bonds that an investor can deal at relatively short notice and for which firm prices exist. The amount outstanding of bond has no influence on the inclusion criteria, but generally for a market to exist the issue must be of a certain size, although this will vary from market to market. As a guide, the smallest issue in the indices in January 2009 was 72 million U.S. dollar. For more detail about how to construct these indices, see JPMorgan Government Bond Index (GBI), January 14, 2002 and Introducing the JPMorgan Government Bond Index-Emerging Markets (EM), January 2006.

With this dataset, our paper is able to include as many as 39 nations around the world, spanning both developed and emerging countries and making ours one of the most comprehensive studies on international asset pricing. The following countries are included (at some time) in the sample: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Columbia, Czech, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Italy, Japan, Korea, Malaysia, Mexico, Netherlands, New Zealand, Peru, Poland, Portugal, Russia, Singapore, South Africa, Spain, Sweden, United Kingdom, United States, Thailand and Turkey. The sample period runs for just over 19 years from December 1989 to February 2009. Monthly data are employed.[53] In total we have 1,244 bond issues.

Table 3-1 is a summary of the country bond characteristics as of 31 December 2008. The market value of all eligible issues is 13,771 billion U.S. dollar. Japanese bonds are the largest group, being about 30 per cent of the total. The U.S. accounts for almost 21 per cent. Local-currency long-term credit ratings, issued by Standard & Poor's, range from the highest AAA (Australia, Austria, Canada, Denmark, Finland, Germany, Ireland, Netherlands, New Zealand, Singapore, Spain, Sweden, U.K. and U.S.) to the lowest B- (Argentina). Average modified duration is 6.26 years.

3.3.1 Bond realized returns

The monthly total return for an individual government bond between period *t-1* and *t* is calculated as

[53] In contrast to the first research paper, which utilizes the weekly data, this paper uses the monthly data instead because 1) we have longer data series and 2) it can be served as another robustness check for our results of the first research paper.

Table 3-1: Summary of the country bond characteristics included in our sample as of December 2008

Country	Market cap (in billion U.S. dollar)	(percent in total)	Local-currency yield (%)	Credit rating	Modified duration (year)
Argentina	0.15	(0.00%)	57.12	B-	1.95
Australia	35.00	(0.25%)	3.69	AAA	4.77
Austria	180.60	(1.31%)	3.65	AAA	6.41
Belgium	306.96	(2.23%)	3.66	AA+	5.84
Brazil	68.13	(0.49%)	12.66	BBB+	2.71
Canada	196.73	(1.43%)	2.94	AAA	7.35
Chile	5.54	(0.04%)	3.32	AA	5.59
China	258.83	(1.88%)	2.19	A+	5.11
Colombia	25.45	(0.18%)	10.26	BBB+	3.73
Czech	30.35	(0.22%)	4.05	A+	5.13
Denmark	73.32	(0.53%)	3.35	AAA	6.32
Finland	56.34	(0.41%)	3.20	AAA	4.42
France	963.74	(6.99%)	3.33	AAA	6.38
Germany	1,087.84	(7.89%)	3.08	AAA	6.17
Greece	224.44	(1.63%)	5.27	A	5.63
Hong Kong	7.23	(0.05%)	0.93	AA+	3.55
Hungary	34.46	(0.25%)	8.88	BBB	3.68
India	127.65	(0.93%)	5.95	BBB-	7.29
Indonesia	20.59	(0.15%)	11.84	BB+	5.51
Ireland	52.83	(0.38%)	4.16	AAA	6.39
Italy	1,041.75	(7.56%)	4.54	A+	6.38
Japan	4,185.80	(30.37%)	1.19	AA	6.56
Korea	164.44	(1.19%)	4.20	A+	4.55
Malaysia	50.32	(0.37%)	3.30	A+	5.04
Mexico	67.89	(0.49%)	8.03	A+	5.56
Netherlands	242.50	(1.76%)	3.41	AAA	5.95
New Zealand	9.06	(0.07%)	4.47	AAA	4.65
Peru	5.42	(0.04%)	7.57	BBB+	7.78
Poland	76.25	(0.55%)	5.34	A	3.95
Portugal	106.66	(0.77%)	3.84	AA-	6.02
Russia	3.45	(0.03%)	9.52	BBB+	2.04
Singapore	44.52	(0.32%)	1.89	AAA	5.45
South Africa	42.65	(0.31%)	7.19	A+	5.54
Spain	380.59	(2.76%)	3.75	AAA	6.08
Sweden	57.07	(0.41%)	2.28	AAA	5.79
Thailand	35.52	(0.26%)	2.72	A	6.04
Turkey	35.66	(0.26%)	16.45	BB	1.64
U.K.	629.53	(4.57%)	3.52	AAA	9.49
U.S.	2,835.65	(20.58%)	2.21	AAA	5.68
Total	13,770.91	(100.00%)			
Mean	336.12		6.55	AA- to A+	5.25
Median	57.07		3.84	A+	5.56

$$r_t^j = \left(\frac{P_t^j + AI_t^j + Coupon_t^j}{P_{t-1}^j + AI_{t-1}^j} \right) - 1, \tag{3.1}$$

where r_t^j is total return of bond j at month t incorporating principal and interest, P_t^j is closing clean price for the bond j at month t, AI_t^j is accrued interest, which is the coupon payment scaled by the ratio of days since the last payment date to the days between last payment and next payment and $Coupon_t^j$ is the coupon payment, if any, of bond j at month t.

3.3.2 Illiquidity measures

Government bonds, on average, provide more data points and arguably more degrees of reliability than corporate bonds. Analysis with government bonds around the world not only provides evidence on global liquidity risk, but also enables us to have a direct liquidity measure. By contrast, previous studies, including Acharya, Amihud and Bharath (2010) and De Jong and Driessen (2006), have used the illiquidity of U.S. Treasury bond as a proxy for the illiquidity of corporate bonds.

Instead, we are able to measure bond illiquidity directly for each bond in each country by its quoted bid/ask spread. At each month t during the study period, the quoted bid/ask spread, c_t^j, is collected for each individual bond j, where c_t^j is the ratio of the quoted bid/ask spread to the bid/ask midpoint. Monthly estimates are obtained as a simple average through the month (to reduce noise and sampling errors) as follows:

$$c_t^j = \frac{1}{n_t^j} \sum_{j=1}^{n_t^j} \frac{Ask_t^j - Bid_t^j}{Mid_t^j}, \tag{3.2}$$

where $Mid_t^j = (Ask_t^j + Bid_t^j)/2$, Ask_t^j and Bid_t^j are mid, ask and bid quoted prices of bond j in month t and $n^j{}_t$ is the number trading days in month t. The data are discarded if there are less than 10 daily quoted bid and ask prices in any month of interest.

3.3.3 Returns on bond portfolios and innovations in market illiquidity

Similar to other empirical works in asset pricing, we group the individual bonds into portfolios in order to reduce the estimation error. Our test portfolios contain the bonds sorted by country of issuance. Not only does this country grouping provide a useful prospective, it also delivers more desirable results from the statistical point of view by helping to avoid the strong factor structure of size and B/M portfolios.[54] To check whether grouping makes a difference to the results, we also perform an equivalent analysis with individual bonds.

The return including coupon payment of a country portfolio i and market-wide return are computed as

$$r_t^i = \sum_{j \text{ in i}} w_t^{ji} r_t^j$$
and (3.3)
$$r_t^M = \sum_{i \text{ in } M} w_t^{iM} r_t^i,$$

where w_t^{ji} is the bond j weight for country portfolio i at week t and w_t^{iM} is the country portfolio i weight for market-wide portfolio M. Value-weighting is used to ensure the

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[54] See Lewellen (2010) for more detail.

investability of the market-wide portfolio.[55] Similarly, the illiquidity of the country *i* portfolio and of the market-wide portfolio *M* are calculated as follows:

$$c_t^i = \sum_{j \text{ in } i} w_t^{ji} c_t^j, \\ c_t^M = \sum_{i \text{ in } M} w_t^{iM} c_t^i. \tag{3.4}$$

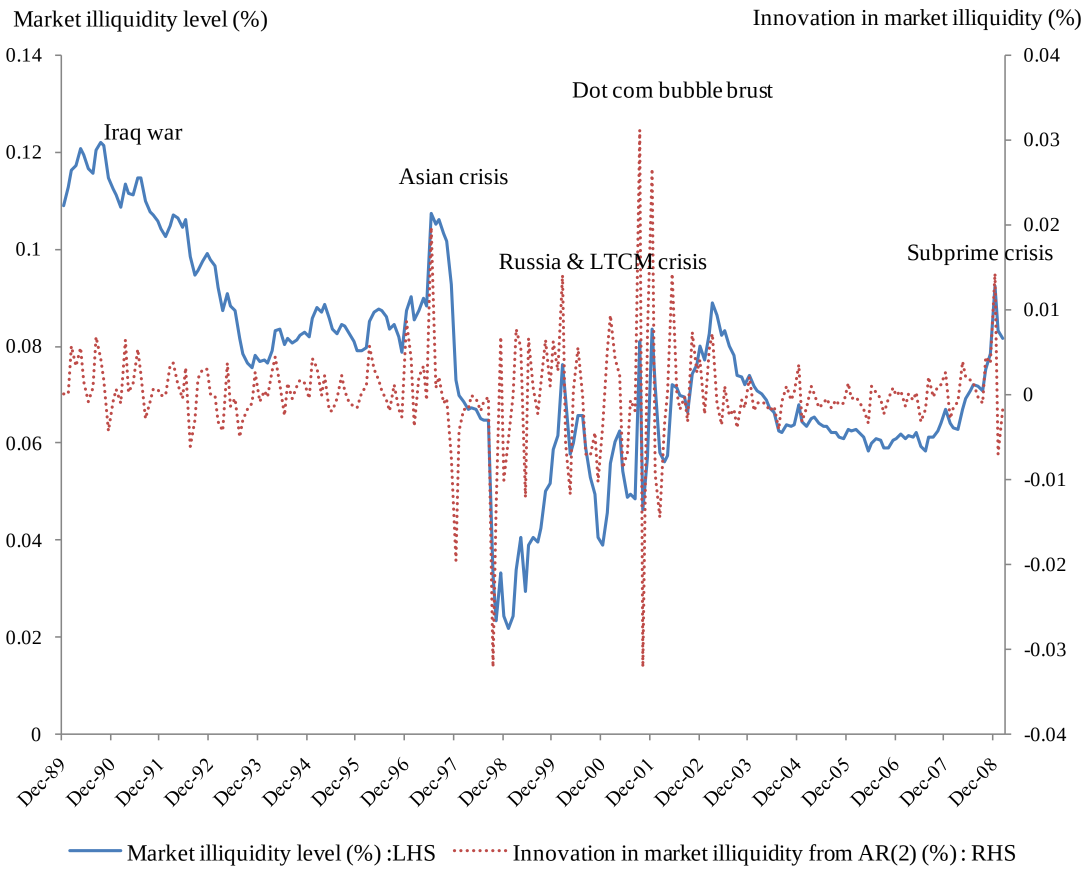
For the whole market, illiquidity cost (i.e., bid/ask spread) has a high monthly autocorrelation of 0.96. Because of this high persistence, we need to compute innovations in illiquidity. Following Pastor and Stambaugh (2003) and Acharya and Pedersen (2005), an AR(2) specification is employed to compute the liquidity innovations for the market portfolio. This AR(2) gives an R^2 of 0.91% for market illiquidity. The remaining autocorrelation of these innovations is very low, at –0.02.[56] We denote innovations in market illiquidity using the AR(2) specification as "*ILLIQ*".

Figure 3-1 shows the time series of the global bond-market illiquidity measured by percentage quoted bid/ask spread and innovations in that series based on the AR(2) specification. The estimated innovations in market illiquidity (*ILLIQ*) are large during periods of global liquidity crisis, for example, the Iraq invasion of Kuwait (August 1990), the Asian Crisis (mid 1997), the Russian and LTCM crises (August-September 1998), the Dot Com bubble burst (2000−2002) and most recently the subprime crisis (September 2007 onwards). These two series, the market illiquidity cost and market liquidity risk factor (*ILLIQ*), will be used in the empirical analyses.

[55] In addition, market weighting provides more stringent asset pricing tests because it overemphasizes large bonds, where liquidity is less concerned.

[56] Using AR(1) instead of AR(2) would greatly increase the autocorrelation of innovation, whereas employing AR(3) would not show much further improvement. We also try an autoregressive moving average (ARMA) process and the results do not change.

Figure 3-1: Time series of monthly global bond-market liquidity
This figure depicts time series of illiquidity cost and its innovation for the global or market-wide portfolio. The liquidity cost is the percentage quoted bid/ask spread and computed by (quoted ask price$_t$ – quoted bid price$_t$)/ mid price$_t$. The innovation is computed using an AR(2) specification. The market portfolio is formed using the value weighting method.



3.3.4 Bond characteristics

We also include a bond's modified duration, illiquidity cost (percentage quoted bid/ask spread) and outstanding market value (in natural logs) as additional explanatory variables in the cross-sectional pricing regression. We expect the modified duration (equivalently to the interest rate term risk) and illiquidity cost to have a positive relationship with the bond expected return. Bond market value is usually cited as another proxy for bond liquidity, so we expect this variable to be negatively related to expected bond returns.

Table 3-2 gives summary statistics of the time-series behaviour of average sample values by year. Even though global bond yields in local-currencies have declined over time in Column 2, the aggregate excess expected bond returns in U.S. dollar after adjusting for default loss in Column 3 move together quite closely with the market illiquidity cost and with the historical financial turmoil (for example, Asian crisis, Dot Com bubble burst and recent subprime crisis).[57] Note that the data on excess bond yield in U.S. dollar adjusted for default loss are only available from 1993 when long-term local-currency sovereign credit rating information was firstly published. The total realized returns in U.S. dollar and aggregate bond maturity show no obvious historical trends. The market value of the portfolios rises strongly from 67 billion U.S. dollar in 1986 to 13,285 billion U.S. dollar in 2008.

[57] See Section 3.4.2 for how to compute the expected excess bond return in U.S. dollar after adjusting for expected default loss.

Table 3-2: Summary statistics on aggregate bond market in the sample

This table reports the year-by-year summary statistics on all eligible bonds included in our sample. The monthly-data sample spans from December 1985 to February 2009. The means (except for total return and bond market capitalization) are reported year-by-year. The numbers in the parentheses are yearly standard deviation. Excess yield in U.S. dollar adjusted for default loss is defined as the local-currency yield minus the one-month U.S. Treasury yield and adjusted 1) into U.S. dollar yield using corresponding currency forward markets with nearest maturity forward contracts and 2) for expected default loss. Market illiquidity or percentage quoted bid/ask spread is calculated as (quoted ask price – quoted bid price)/quoted bid price, which reflects the illiquidity cost of the global bond markets. Total market return is the realized return taking into account of capital gain, coupon and accrued interest. All are market-weighted. Market cap is the total market value of all bonds in the sample. Where data are not available, NA is noted.

Year	Yield in local currency (%)		Excess yield in U.S.$ adjusted for default loss (%)		Market illiquidity (%) (% bid/ask spread)		Total market return in U.S.$ (%)		Maturity (year)	Market cap (billion U.S. dollar)
1986	7.50	(1.86)	NA		NA		18.82	(9.43)	7.86	67.57
1987	7.66	(2.34)	NA		NA		13.27	(7.77)	7.58	75.28
1988	8.02	(1.007)	NA		NA		5.05	(5.32)	7.30	82.72
1989	8.18	(0.94)	NA		NA		6.81	(6.46)	7.42	119.69
1990	9.01	(0.82)	NA		0.12	(0.01)	11.39	(6.33)	7.07	126.61
1991	8.26	(1.19)	NA		0.11	(0.01)	14.73	(7.54)	7.23	179.53
1992	7.60	(0.92)	NA		0.10	(0.02)	4.63	(6.75)	7.31	223.48
1993	6.17	(1.54)	0.12	(0.05)	0.08	(0.03)	11.74	(3.56)	7.31	312.03
1994	7.10	(2.59)	0.19	(0.08)	0.08	(0.01)	1.38	(3.23)	6.91	339.45
1995	6.76	(1.96)	0.88	(0.11)	0.08	(0.01)	18.10	(6.30)	7.13	488.10
1996	6.13	(1.05)	1.13	(0.05)	0.08	(0.01)	4.31	(3.47)	6.95	536.49
1997	5.62	(0.93)	1.02	(0.08)	0.09	(0.04)	1.52	(5.19)	7.85	900.65
1998	4.67	(1.30)	0.57	(0.06)	0.05	(0.07)	14.29	(6.01)	8.18	1,205.26
1999	4.65	(1.15)	0.82	(0.07)	0.04	(0.04)	-4.82	(5.02)	8.01	1,222.24
2000	4.83	(0.77)	0.32	(0.11)	0.06	(0.04)	2.52	(7.49)	8.26	1,552.85
2001	4.13	(0.76)	1.56	(0.27)	0.06	(0.04)	-0.67	(6.62)	8.00	1,933.82
2002	3.87	(1.24)	3.08	(0.07)	0.07	(0.03)	18.74	(7.22)	7.82	2,835.09
2003	3.31	(0.680)	2.94	(0.07)	0.08	(0.02)	14.51	(8.74)	7.62	3,872.52
2004	3.45	(0.557)	2.66	(0.16)	0.07	(0.01)	10.63	(6.98)	7.64	5,175.19
2005	3.21	(0.455)	0.79	(0.10)	0.06	(0.01)	-5.89	(4.61)	7.87	5,896.48
2006	3.72	(0.554)	0.12	(0.04)	0.06	(0.01)	6.67	(4.86)	7.95	7,644.37
2007	3.95	(0.509)	0.46	(0.15)	0.06	(0.01)	10.70	(5.46)	8.10	9,966.78
2008	3.64	(1.362)	2.99	(0.16)	0.07	(0.03)	9.84	(10.73)	8.24	13,285.91

3.4 Unconditional Liquidity Risk and Asset Pricing Models

We study how liquidity risk affects expected bond returns using the standard Fama-MacBeth (1973) method for our 39-country government bond portfolios. First, we estimate betas from rolling time-series regressions. Then, in the second stage, we estimate cross-section regressions for each month and compute the sample means of the estimated slope coefficients (i.e., the risk premiums) associated with each of the different betas.

3.4.1 Unconditional liquidity risk – 1st stage time-series estimations

At first, the two-factor model with liquidity factor is

$$r_t^i - r_t^f = \alpha^i + \beta^{DEF,i} DEF_t + \beta^{TERM,i} TERM_t + \beta^{ILLIQ,i} ILLIQ_t + \varepsilon_t^i, \tag{3.5}$$

where r_t^i is the monthly bond return in U.S. dollar on the country *i* bond portfolio at time *t*, r^f is the one-month U.S. Treasury-bill return, which represents the risk-free rate, $\beta^{DEF,i}$ and $\beta^{TERM,i}$ represent the default beta and term beta, respectively and $\beta^{ILLIQ,i}$ is the liquidity beta.[58] *DEF* and *TERM* are proxies for bond default risk and interest rate term risk factors respectively.[59] *DEF* is defined as the difference between the monthly government bond return on a value-weighted market portfolio of all non-investment grade government bonds (below BBB) with at least ten years to maturity and the monthly government bond return on a value-weighted portfolio of all investment grade

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[58] This liquidity beta is $\beta^{3,i}$, which captures the exposure of asset *i* to market-wide illiquidity, one of three liquidity risks in Acharya and Pedersen (2005). As suggested by the first research paper, using three separate liquidity betas is not necessary since all three liquidity betas are highly correlated.

[59] The same risk factors as used in Fama and French (1993) and Gebhardt, Hvidkjaer and Swaminathan (2005) for the U.S. corporate bonds.

government bonds (AAA to BBB) with at least ten years to maturity.[60] *TERM* is defined as the difference between the monthly government bond return on a value-weighted portfolio of all bonds with at least ten years to maturity and return on one-month U.S. Treasury-bills, which is from the CRSP and also used as the risk-free rate throughout the paper. *ILLIQ* is the market liquidity risk factor as described in Section 3.3.3.

All betas are estimated in Equation (3.5) using the prior 50-month rolling window. Data are discarded if there are less than 20 observations before the test month. Since we require 50 months of prior data to estimate betas, our regressions start from January 1995 and run to February 2009, while our whole sample starts from December 1989.

Table 3-3 gives the correlations of risk factors used in Equation (3.5). It shows that *TERM* is highly correlated with market return (a correlation of 0.89), while *DEF* has a correlation of –0.29 with market return. The correlations between other factors and market returns are small. The high correlation between *TERM* and the bond market return and high correlation between *DEF* and the bond market return support the finding of Gebhardt, Hvidkjaer and Swaminathan (2005) that the market factor has almost no explanatory power for corporate bond returns when the default and term risk factors are included. The table also shows that the simple correlations of liquidity risk factor (*ILLIQ*) with market returns and other factors (*DEF*, *TERM*, global bond return volatility and U.S. equity market returns) are small, which help provide a clean interpretation of the liquidity effects.

[60] Long-term local-currency issue rating published by Standard & Poor's is utilized.

Table 3-3: Correlations of the time-series of risk factors

This table shows the correlations of all market factors used in our study. The data are from December 1985 to February 2009. $r^{MKT} - r^f$ is the value-weighted monthly excess return on all government bonds in the GBI and EM over the one-month U.S. Treasury-bill return. *DEF* is the difference between value-weighted monthly return on all non-investment grade bonds with at least ten years to maturity and that of all investment grade bonds. *TERM* is the difference between the monthly government bond return on a value-weighted portfolio of all bonds with at least ten years to maturity and the monthly one-month U.S. Treasury-bill return. *ILLIQ* is the innovation in the bond market illiquidity. VOL^{BOND} is the global bond return volatility. $r^{USEQ\_MKT} - r^f$ is the value-weighted monthly excess return on all common shares listed on NYSE and AMEX over the one-month U.S. Treasury-bill return.

	r^{MKT} - r^f	*DEF*	*TERM*	*ILLIQ*	VOL^{BOND}	r^{USEQ_MKT} - r^r
$r^{MKT} - r^f$	1.00	-0.29	0.89	-0.10	0.14	0.02
DEF		1.00	-0.35	0.15	-0.07	0.30
TERM			1.00	-0.08	0.05	-0.02
ILLIQ				1.00	0.00	-0.06
VOL^{BOND}					1.00	0.02
$r^{USEQ\_MKT} - r^r$						1.00

Table 3-4 reports the betas ($\beta^{ILLIQ,i}$, $\beta^{DEF,i}$ and $\beta^{TERM,i}$) for country bond portfolio *i* estimated from Equation (3.5) using the whole sample, average expected excess bond returns ($E(r^i_t - r^f_t)$) (see Session 3.4.2 for the estimation method) and average quoted bid/ask spreads ($E(c^i_t)$). The country portfolio is sorted in descending order of estimated liquidity risk beta ($\beta^{ILLIQ,i}$). In Table 3-4, we expect country bond portfolios with higher liquidity risk (i.e., more negative values for estimated liquidity risk beta) and higher illiquidity cost (i.e., larger bid/ask spreads) to have higher expected excess returns. China has the lowest liquidity risk (β^{ILLIQ} = +1.72) and Argentina the largest (β^{ILLIQ} = –30.99). The correlation between unconditional $\beta^{ILLIQ,i}$ and c^i_t is –0.22, showing that countries with higher liquidity risk also tend to have higher illiquidity costs. A sound feature of the table is that the Euro-zone countries (for example, France, Germany, Spain, etc.) have similar liquidity betas.

Table 3-4: Country bond portfolio characteristics: whole sample averages of estimated betas, expected excess returns and bid/ask spreads

This table reports betas estimated from Equation (3.5) using the whole monthly data from January 1990 to February 2009. For betas, $\beta^{ILLIQ,i}$, $\beta^{DEF,i}$ and $\beta^{TERM,i}$ represents the liquidity, default and term betas for the country bond portfolio i. $E(r^i_t - r^f_t)$ is the average expected excess bond returns after adjusting for expected default loss. $E(c^i_t)$ is the average percentage bid/ask spread. Countries are sorted to their values of $\beta^{ILLIQ,i}$.

Country	$\beta^{ILLIQ,i}$	$\beta^{DEF,i}$	$\beta^{TERM,i}$	$E(r^i_t - r^f_t)$	$E(c^i_t)$	Date when bid/ask data first available
China	1.72	0.04	0.25	0.24	0.02	Mar-05
Czech	1.07	0.12	1.08	0.18	0.10	Nov-01
India	0.71	0.38	0.49	0.17	0.07	Nov-02
Hungary	0.63	0.46	1.12	0.11	0.20	May-02
Thailand	0.39	0.46	1.02	0.12	0.28	Jan-01
Korea	0.35	0.41	0.82	0.21	0.19	Aug-02
Denmark	0.34	0.00	0.85	0.15	0.08	May-94
Malaysia	0.29	-0.82	0.10	0.08	0.07	Jun-03
Sweden	0.28	0.05	0.81	0.13	0.08	Jan-98
Italy	0.27	0.00	0.88	0.12	0.03	Nov-98
Austria	0.26	0.09	1.11	0.11	0.09	Dec-97
Spain	0.25	-0.01	0.87	0.11	0.08	Aug-97
Portugal	0.22	-0.02	0.83	0.11	0.08	Sep-98
Finland	0.22	0.04	0.83	0.10	0.06	May-00
France	0.22	-0.04	0.90	0.11	0.03	Dec-01
Ireland	0.20	0.01	0.97	0.11	0.08	Jun-99
Germany	0.20	-0.02	0.86	0.11	0.02	Jan-99
Netherlands	0.19	-0.01	0.86	0.11	0.03	Dec-01
Hong Kong	0.19	0.00	0.30	0.10	0.15	Jan-01
Belgium	0.18	-0.01	0.86	0.11	0.07	Jul-99
New Zealand	0.15	0.18	0.83	0.39	0.21	Jan-93
Canada	0.01	0.10	0.62	0.15	0.04	Dec-89
Poland	-0.02	0.54	0.84	0.18	0.19	Feb-01
Greece	-0.02	0.16	0.94	0.13	0.11	Jul-98
Singapore	-0.02	0.10	0.54	0.15	0.10	Jul-00
US	-0.07	-0.03	0.44	0.14	0.05	Nov-89
Australia	-0.09	0.19	0.73	0.30	0.21	Sep-98
South Africa	-0.15	0.69	1.03	0.08	0.13	Feb-95
Japan	-0.19	0.07	0.39	0.12	0.13	Mar-93
UK	-0.24	-0.08	0.85	0.18	0.04	Sep-02
Brazil	-0.95	0.45	0.03	0.23	0.14	Jul-96
Indonesia	-1.19	0.66	0.60	0.09	0.34	Apr-03
Mexico	-2.00	0.52	0.28	0.09	0.31	Jan-93
Russia	-2.97	-0.07	0.19	0.07	0.18	Mar-06
Colombia	-2.98	0.31	0.53	0.18	0.12	Sep-05
Turkey	-3.82	0.64	0.95	0.12	0.14	Apr-06
Chile	-4.01	0.11	0.29	0.04	0.21	Dec-05
Peru	-5.66	0.40	0.52	0.19	0.75	Oct-06
Argentina	-30.99	0.11	1.14	0.32	0.17	Jun-06

3.4.2 Unconditional liquidity risk – 2nd stage cross-section regressions

The main question to be addressed is whether the liquidity risk is important after controlling for systematic default risk, interest rate term risk and other bond characteristics. We do this with the second stage regression, in which we estimate an unconditional cross-sectional regression of the expected excess return on the factor loading (betas) estimated from Equation (3.5):

$$E(r_t^i - r_t^f) = \phi + \lambda^{DEF}\hat{\beta}^{DEF,i} + \lambda^{TERM}\hat{\beta}^{TERM,i} + \lambda^{ILLIQ}\hat{\beta}^{ILLIQ,i} + B^{L,i\prime}\lambda_L + \eta^i, \qquad (3.6)$$

where ϕ represents an estimated pricing error, λ^{DEF} ,λ^{TERM} and λ^{ILLIQ} are the risk premiums associated with the default risk, term risk and liquidity risk respectively and $E(r^i_t - r^f_t)$ is the expected (forward-looking) excess bond return after adjusting for expected default loss.[61] We also include each bond portfolio's characteristics in the cross-sectional analysis: $B^{L,i\prime}$ is a three dimensional vector of bond characteristics. In some alternative specifications, we include the percentage quoted bid/ask spread for each country bond portfolio since both Acharya and Pedersen (2005) and the first research paper find that the liquidity level is important in explaining the expected returns for financial assets. The bond's modified duration and the bond's market value scaled by taking natural log are also included in some specifications of Equation (3.6).

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[61] It is important to note that unlike λ^{DEF} and λ^{TERM}, λ^{ILLIQ} or liquidity risk premium should be <u>negative</u> because a high β^{ILLIQ} bond gives higher returns when market illiquidity is high, i.e., this bond has a lower liquidity risk, so it is more attractive to investors and therefore its price is higher and expected return is lower. If we measure liquidity rather than illiquidity, λ_{ILLIQ} should be positive. To be consistent with Chapter 2, we again measure illiquidity not liquidity here.

The expected excess bond return after adjusting for expected default loss is computed by a method similar to that used by Campello, Chen and Zhang (2008) with the following equation:

$$E(r_t^i - r_t^f) = (y_t^i - r_t^f) + EDL_t^i + EFX_t^i, \tag{3.7}$$

where y^i_t is the current yield to maturity. EDL^i_t, or expected default loss rate, is defined as −default probability · (1 − recovery rate)/dt < 0.[62] The equation is the same as that used in the first research paper (see Equation (2.12)) except for the extra term, EFX^i_t, which is defined as the expected foreign exchange gain/loss in terms of U.S. dollar. This adjustment of forward-looking foreign exchange returns is required because our collected government bond yields are quoted in their local-currencies. We extract the expected currency gain/loss from the currency forward market. From JP Morgan, the forward points on a given currency against U.S. dollar at the maturity of 1, 2, 3, 4, 5, 7 and 10 years are collected on a monthly basis.[63] We then compute the expected currency loss/gain for a given maturity that most closely matches each bond's duration.

Table 3-5 reports the cross-section regression results of the unconditional factor models with liquidity risk, where standard errors are computed using the Newey and West

[62] We compute the expected default loss rate as in Section 2.4.5 except that we use the local-currency rating rather foreign-currency sovereign credit rating since our test assets are local-currency government bonds.

[63] The number of basis points are added to or subtracted from the current spot rate to determine the forward rate. When points are added to the spot rate, there is a forward point premium; when points are subtracted from the spot rate, there is a points discount. The forward points are determined by prevailing interest rate between two countries. For example, if the current spot rate of the U.S. dollar/GBP is 1.60 and the five-year forward rate is 1.62, the number of forward points is 200 basis points.

Table 3-5: Country portfolios and Fama-MacBeth regression

This table reports the time-series averages of coefficients of each beta obtained in a cross-sectional regression. A two-step Fama-Macbeth (1973) procedure is employed. First, estimates of the systematic risk (betas) are obtained by running a regression of bond's monthly returns, r^i_t on different risk factors. The models are alternative cases of the following equation:

$$r_t^i - r_t^f = \alpha^i + \beta^{DEF,i} DEF_t + \beta^{TERM,i} TERM_t + \beta^{ILLIQ,i} ILLIQ_t + \beta^{MKT,i}(r_t^{MKT} - r_t^f),$$

where α^i is the intercept, r^f_t is the risk-free rate, $\beta^{DEF,i}$ is the default beta of the *i*th bond, DEF_t is the difference between value-weighted monthly return on all non-investment grade bonds with at least ten years to maturity and that of all investment grade bonds, $\beta^{TERM,i}$ is the term beta, $TERM_t$ is the difference between the monthly government bond return on a value-weighted portfolio of all bonds with at least ten years to maturity and the monthly one-month U.S. Treasury-bill returns, $\beta^{ILLIQ,i}$ is the liquidity beta, $ILLIQ_t$ is the innovation in the market illiquidity, $\beta^{MKT,i}$ is the bond market beta and r_t^{MKT} is the value-weighted bond market monthly return. The betas are estimated over 50 months. Our sample starts from December 1985 to February 2009.

In the second stage, expected bond returns adjusted for default loss, $E(r^i_t - r^f_t)$, are regressed on the estimated betas from Equation (3.5) and other three bond individual characteristics, which are the bond illiquidity cost (c^i_t), bond maturity (in year) and natural log of the U.S. dollar market value of bond issue in the different cross-sectional models for each month in the sample period. The betas to be used in each monthly cross-sectional regressions are estimated using data from the period preceding each month and they are "rolling" betas. For each month, the cross-sectional regressions are of the following alternatives:

$$E(r_t^i - r_t^f) = \phi + \lambda^{DEF}\hat{\beta}_t^{DEF,i} + \lambda^{TERM}\hat{\beta}_t^{TERM,i} + \lambda^{ILLIQ}\hat{\beta}_t^{ILLIQ,i} + \lambda^{MKT}\hat{\beta}_t^{MKT,i} + \gamma^1 c_t^i + \gamma^2 maturity_t^i$$
$$+\gamma^3 \ln(bond\ market\ value)_t^i.$$

t-statistics from Newey West (1987) are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively.

Variable	5.1	5.2	5.3	5.4	5.5	5.6
Intercept (ϕ)	0.149[c]	0.139[c]	0.105[c]	0.117[c]	0.110[c]	0.134[c]
	(13.68)	(12.68)	(6.88)	(5.11)	(7.55)	(5.69)
DEF beta ($\hat{\beta}_t^{DEF,i}$)	0.017	0.001	0.069[c]	0.079[c]	0.077[c]	0.070[c]
	(1.33)	(0.13)	(3.62)	(3.99)	(3.66)	(2.81)
TERM beta ($\hat{\beta}_t^{TERM,i}$)	0.015	0.009	0.052[b]	0.054[b]	0.045[c]	0.014
	(1.07)	(0.64)	(2.38)	(2.45)	(1.93)	(0.43)
*Liquidity beta *100*($\hat{\beta}_t^{ILLIQ,i}$)		-0.023[a]	-0.022[b]	-0.028[c]	-0.028[b]	-0.029[b]
		-(1.94)	-(2.46)	-(2.90)	-(2.31)	-(2.31)
Bond market beta ($\hat{\beta}_t^{MKT,i}$)					0.013	-0.001
					(0.97)	-(0.05)
Illiquidity cost (c_t^i)			0.179[c]	0.175[c]	0.182[c]	0.165[c]
			(3.16)	(2.96)	(3.98)	(3.27)
Modified duration				0.007[b]		0.009[b]
				(2.07)		(2.33)
ln(bond market value)				-0.009[b]		-0.010[c]
				-(2.36)		-(2.82)
R^2	0.195	0.282	0.444	0.503	0.474	0.527
Adjusted R^2	0.109	0.161	0.219	0.145	0.178	0.135
Number of observations	4,362	4,362	3,633	3,633	3,633	3,633

(1987) method, which adjusts for heteroskedasticitiy and autocorrelations. Model 5.1 is the regression containing only the default risk and term risk. Although the risk premia attached to both risks (λ^{DEF} and λ^{TERM}) are positive, neither is statistically significant. The R^2 is fairly low at 0.195, but that is similar in magnitude to those reported by both Fama and French (1993) and Gebhardt, Hvidkjaer and Swaminathan (2005) for the same specification using U.S. corporate bonds.

In model 5.2, liquidity risk (β^{ILLIQ}) is included. There is a large increase in the R^2 to 0.282. The coefficient of $\hat{\beta}^{ILLIQ}$ is –0.023 and significant at the 10% level. It is negative, which is expected, because investors should require lower expected returns to hold an asset with a high return in times of market illiquidity. Alternatively, the more negative is the exposure of the asset to market illiquidity, the greater is the expected return.[64] The default beta and term beta remain both positive and insignificant.

The regression in model 5.3 is the same as in model 5.2, but illiquidity cost (c_t) is added-in, being measured by the percentage bid/ask spread. As expected, the coefficient of c_t^i is positive and significant at the 1% level. Interestingly, the *DEF* and *TERM* risks now become positive and significant, but liquidity risk beta (–0.022) remains significant. This suggests that the liquidity level might be an omitted variable in the previous two regressions. One implication of the theoretical model is that the coefficient on illiquidity cost should reflect the difference between estimation periods (in this case, monthly) and investors' holding periods. From our results, the estimated coefficient of c_t is 0.179, which is equivalent to an average holding period of about 1/0.179 ≅ 5.6 months, i.e., an

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[64] This is the same liquidity mechanism investigated by Pastor and Stambaugh (2003) and Martinez, Nieto, Rubio and Tapia (2005) for the stock returns.

annual turnover of about 2.1. This is consistent with the historical turnover reported for domestic government bond markets.[65]

In model 5.4, two bond characteristics– bond modified duration and natural log of market value of bond issue– are entered into the pricing equation. Both bond modified duration and market value, which have usually been considered as proxies for interest rate term risk and liquidity level respectively in the previous literature, are significant. In fact, they have the correct signs even in the presence of the illiquidity cost, which is the more direct measure of liquidity. The shorter is bond maturity and the greater is bond market value, the lower is the interest rate term risk and the higher is bond liquidity, which leads to lower required bond returns. However, the inclusion of both bond characteristics does not produce any improvement in terms of the adjusted R^2, which is lower for model 5.4 than that for model 5.3.

Models 5.5 and 5.6 show that adding-in the market (CAPM) beta factor hardly changes any of the findings. The estimated market risk premium is very close to zero in both regressions (0.013 and –0.001 respectively) and not significant. This is consistent with previous empirical findings that the market factor has almost no explanatory power for corporate bond returns, especially when the default and term risk factors are included.[66]

Table 3-6 reports the time-series average of correlations among the dependent variables used in the cross-sectional regressions in Table 3-5. It shows that the market beta has a

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[65] Knight (2006) reports an average annual turnover of about two in the local bond markets across many countries.

[66] Gebhardt, Hvidkjaer and Swaminathan (2005) find that empirically the market factor has almost no explanatory power for corporate bond returns in the presence of default and term risk factors.

correlation of –0.90 with the term beta, so these variables are close substitutes. That explains why market beta has no significant input when the term beta is present.

Table 3-6: Average cross-section correlations of estimated risk loadings over our sample period

	Market beta	*Liquidity beta*	*DEF beta*	*TERM beta*	*Illiquidity cost*
Market beta	1.00	0.06	-0.31	-0.90	-0.22
Liquidity beta		1.00	-0.12	-0.03	-0.06
DEF beta			1.00	0.43	0.33
TERM beta				1.00	0.22
Illiquidity cost					1.00

3.4.3 Economic significance of empirical results

The results so far are statistically impressive. For example, model 5.4 can explain over 50% of the cross-sectional variance of expected bond excess returns. However, the results also show that the economic significance of liquidity risk is small relative to that of liquidity level. As an example, consider Argentinian and Chinese bonds, for which the difference in unconditional U.S. dollar expected excess return is 1.00% (3.86% – 2.86%) per annum.[67] Using the results from model 5.3 in Table 3-5, the difference in annualized expected excess returns between these two countries due to liquidity risk (β^{ILLIQ}) is $[(-0.022/100)\cdot 12\cdot(\beta^{ILLIQ,Argentina} - \beta^{ILLIQ,China})] = 0.09\%$ per annum, whereas the difference in annualized expected excess returns due to the expected level of illiquidity cost (c^i) is estimated to be $[(0.179)\cdot 12\cdot(c^{Argentina} - c^{China})] = 0.32\%$ per annum. Together, liquidity risk and liquidity level can explain as much as 0.41% per annum of

[67] Argentina and China are chosen because they are respectively the highest and lowest liquidity risk countries as measured by the unconditional magnitude of β^{ILLIQ} over our sample reported in Table 3-4. See top and bottom rows of the table.

the 1.00% credit spread between Argentinian and Chinese bonds. The rest is mostly captured by the difference in *TERM* betas (β^{TERM}), which explains about 0.55% per annum. The *DEF* beta (β^{DEF}) contributes only about 0.06% per annum in explaining the credit spread between these two countries.

Even though there is strong statistical evidence that liquidity level and global liquidity risk are priced in the domestic government bond markets around the world, the economic significance of liquidity risk is only about one quarter as large as that of liquidity level in this unconditional analysis.

3.4.4 Robustness tests

As a test of robustness, we experiment with other three risk factors in our pricing equation, Equation (3.6), to see whether the liquidity effect remains important. The additional market factors include 1) aggregate bond volatility, 2) U.S. equity market returns and 3) liquidity in the U.S. equity market. Bond volatility is another proxy for liquidity risk because volatility is expected to have a positive relation with bid/ask spreads or a negative impact on liquidity. Intuitively, an increase in bond volatility poses higher risks for dealers, who have to hold less than fully-diversified portfolios, therefore they need to be compensated directly through a higher bid/ask spread. With respect to U.S. equity factors, we would like to see whether the U.S. equity market– both in terms of its returns and its liquidity– is a driving force in pricing domestic bonds around the world. When U.S. stocks fall in price or become illiquid, does that affect domestic bond markets worldwide?

For the estimation of monthly volatility of the aggregate bond market, we employ an exponentially-weighted moving average (EWMA) as used, for example, by Riskmetrics.[68] For the U.S. stock market returns, we use monthly data from the Center for Research in Security Prices (CRSP). For the U.S. market illiquidity, we employ the factor estimated by Pastor and Stambaugh (2003).[69] Note that Pastor and Stambaugh measure liquidity and we focus on illiquidity, so we simply switch the signs of the measures.

Results from cross-sectional regressions with these extra risk factors are given in Table 3-7. They show that 1) the liquidity beta is the only risk factor that is significantly priced in all cross-sectional pricing equations and 2) in some specifications, domestic government bonds, which are grouped by country of issuance, have a significant exposure to the bond volatility beta, U.S. equity market beta and U.S. equity market illiquidity beta.

In model 7.1 when bond volatility beta ($\hat{\beta}_t^{VOL^{BOND}}$) is included, only an exposure to the bond liquidity risk is priced. In model 7.2, when we add-in both U.S. equity market beta ($\hat{\beta}_t^{USEQ\_MKT}$) and U.S. equity market illiquidity beta ($\hat{\beta}_t^{PS,i}$), they are not significantly priced and the price of bond volatility risk ($\hat{\beta}_t^{VOL^{BOND}}$) becomes significantly negative.[70]

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[68] The EWMA approach gives more weight to recent observations than to older ones. The smoothing or decay parameter used in this paper is lambda λ = 0.97, with rolling window of 24 months.

[69] The return reversal measure of Pastor and Stambaugh (2003) reflects that the price changes with large trading volume tend to be reversed when market-wide liquidity is low.

[70] We expect a negative sign because investors should require less expected returns for holding a security that performs well in times of high market volatility.

Table 3-7: Country portfolios and Fama-MacBeth regression with additional risk factors

This table reports the time-series averages of coefficients of each beta obtained in a cross-sectional regression. A two-step Fama-Macbeth (1973) procedure is employed. First, estimates of the systematic risk (betas) are obtained by running a regression of bond's monthly returns, r^i_t on different risk factors. The models are alternative cases of the following equation:

$$r_t^i - r_t^f = \alpha^i + \beta^{DEF,i} DEF_t + \beta^{TERM,i} TERM_t + \beta^{ILLIQ,i} ILLIQ_t + \beta^{MKT,i}(r_t^{MKT} - r_t^f) + \beta^{VOL^{BOND},i} VOL_t^{BOND}$$
$$+ \beta^{USEQ\_MKT,i}(r_t^{USEQ\_MKT} - r_t^f) + \beta^{PS,i} PS_t,$$

where α^i is the intercept, r^f_t is the risk-free rate, $\beta^{DEF,i}$ is the default beta of the ith bond, DEF_t is the difference between value-weighted monthly return on all non-investment grade bonds with at least ten years to maturity and that of all investment grade bonds, $\beta^{TERM,i}$ is the term beta, $TERM_t$ is the difference between the monthly government bond return on a value-weighted portfolio of all bonds with at least ten years to maturity and the monthly one-month U.S. Treasury-bill returns, $\beta^{ILLIQ,i}$ is the liquidity beta, $ILLIQ_t$ is the innovation in the market illiquidity, $\beta^{MKT,i}$ is the bond market beta, r_t^{MKT} is the value-weighted bond market monthly return and $\beta^{VOL^{BOND},i}$ is the bond market volatility beta, VOL_t^{BOND} is the aggregate bond market volatility, $\beta^{USEQ\_MKT,i}$ is the U.S. equity market beta, $r_t^{USEQ\_MKT}$ is the value-weighted U.S. equity market return, β^{PS} is the U.S. equity market liquidity beta and PS_t is the monthly measure of innovation in illiquidity in the U.S. equity market calculated by Pastor and Stambaugh (2003). The betas are estimated over 50 months. Our sample starts from December 1985 to February 2009.

In the second stage, expected bond returns adjusted for default loss, $E(r^i_t - r^f_t)$ are regressed on the estimated betas from Equation (3.5) and other three bond individual characteristics, which are the bond illiquidity cost (c^i_t), bond maturity (in year) and natural log of the U.S. dollar market value of bond issue in the different cross-sectional models for each month in the sample period. The betas to be used in each monthly cross-sectional regressions are estimated using data from the period preceding each month and they are "rolling" betas. For each month, the cross-sectional regressions are of the following alternatives:

$$E(r_t^i - r_t^f) = \phi + \lambda^{DEF}\hat{\beta}_t^{DEF,i} + \lambda^{TERM}\hat{\beta}_t^{TERM,i} + \lambda^{ILLIQ}\hat{\beta}_t^{ILLIQ,i} + \lambda^{MKT}\hat{\beta}_t^{MKT,i} + \lambda^{VOL^{BOND}}\hat{\beta}_t^{VOL^{BOND},i} + \lambda^{USEQ\_MKT}\hat{\beta}_t^{USEQ\_MKT,i}$$
$$+ \lambda^{PS}\hat{\beta}_t^{PS,i} + \gamma^1 c_t^i + \gamma^2 maturity_t^i + \gamma^3 \ln(bond\ market\ value)_t^i.$$

t-statistics from Newey West (1987) are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively.

Table 3-7 (continued)

Variable	7.1	7.2	7.3	7.4	7.5	7.6
Intercept (ϕ)	0.062	0.164[c]	0.120[c]	0.085[c]	0.123[c]	0.094[c]
	(0.82)	(12.11)	(8.19)	(6.71)	(8.23)	(3.70)
*Liquidity beta *100*($\hat{\beta}_t^{ILLIQ,i}$)	-0.038[c]	-0.023[b]	-0.015[c]	-0.031[b]	-0.052[c]	-0.590[c]
	-(2.48)	-(2.31)	-(2.77)	-(2.26)	-(3.81)	-(4.16)
DEF beta ($\hat{\beta}_t^{DEF,i}$)					0.102[c]	0.116[c]
					(3.42)	(3.81)
TERM beta ($\hat{\beta}_t^{TERM,i}$)					0.032	0.047[c]
					(1.26)	(3.47)
Illiquidity cost (c_t^i)	0.295	0.006	0.158[c]	0.536[b]	0.115[c]	0.141[c]
	(1.36)	(0.11)	(2.98)	(2.07)	(3.85)	(3.47)
Modified duration						0.003
						(0.89)
Ln(*bond market value*)						-0.000
						(0.04)
Bond volatility beta($\hat{\beta}_t^{VOL^{BOND},i}$)	0.017	-0.039[c]			0.003	0.004
	(0.08)	-(3.01)			(1.10)	(1.46)
U.S. Market beta ($\hat{\beta}_t^{USEQ\_MKT,i}$)		0.051	0.120[c]	0.092[a]	0.064[c]	0.068[c]
		(1.50)	(5.09)	(1.91)	(3.85)	(3.50)
U.S. equity liquidity beta ($\hat{\beta}_t^{PS,i}$)		-0.000		-0.002[c]	-0.002[c]	-0.002[c]
		-(0.38)		-(2.97)	-(3.85)	(3.69)
R^2	0.457	0.573	0.420	0.511	0.600	0.664
Adjusted R^2	0.205	0.224	0.138	0.123	0.290	0.302
Number of observations	3788	3738	3,738	3,738	3,633	3,633

Nonetheless, both coefficients on $\hat{\beta}_t^{USEQ\_MKT}$ and $\hat{\beta}_t^{PS}$ are significant with expected signs in models 7.3, 7.4, 7.5 and 7.6. The risk premium of U.S. equity returns is positive and significant. The exposure to illiquidity shocks in the U.S. equity market is also important and has the expected negative sign, indicating that investors are willing to accept a lower yield on a bond with a high return in times of U.S. stock market illiquidity. In other words, a bond has more hedging value if it performs well when the U.S. equity market becomes illiquid and such a bond requires a lower expected return. In models 7.5 and 7.6, the same empirical results are found when *DEF* and *TERM* risk factors and bond characteristics are entered into the pricing equation. The bond liquidity beta ($\hat{\beta}_t^{ILLIQ}$) is the only explanatory variable that remains significant in every model and has the expected sign. Table 3-7 therefore confirms that the effect of liquidity risk is robust to the inclusion of a number of other potentially relevant risk factors and bond characteristics.

As another robustness check, we have repeated the previous tests using individual bonds (rather than country bond portfolios) as test assets. Liquidity is still priced. Moreover, liquidity risk becomes relatively more important than liquidity level for bonds in the emerging economies. Appendix A provides detailed discussions and results.

In summary, we find some evidence that bond volatility, U.S. equity returns and U.S. equity volatility are important in the cross-sectional pricing of global bonds.[71] For 39 countries, domestic bond credit spreads over U.S Treasury reflect a global risk factor, proxied by the U.S. stock market. Table 3-7 also suggests that illiquidity can spill over from the U.S. stock market to domestic bond markets around the world. In addition, the impact of bond liquidity risk is not sensitive to the choice of market risk factor or of global illiquidity factor.

[71] This finding is consistent with Diaz-Weigel and Gemmill (2006), Longstaff, Mithal and Nes (2005) and Min, Lee, Nam, Park and Nam (2003). They report that the credit spread in the emerging markets has the global and/or regional factors such as the U.S. stock market or U.S. Treasury market. Lee (2010) also finds the U.S. equity market is an important driving force of global liquidity risk for equity.

3.5 Conditional Liquidity Risk and Asset Pricing Models

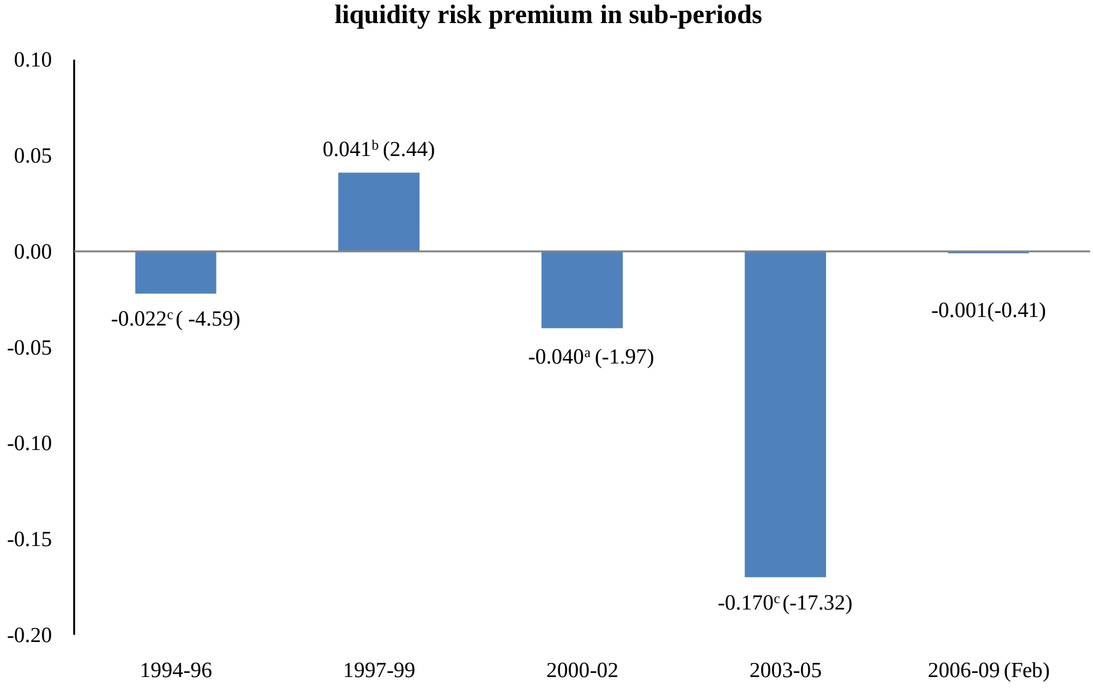
In the previous section, even though liquidity risk was significantly related to expected government bond returns in the cross-section of 39 countries, its economic impact was rather small. This might be because the estimated risk premia in the second stage cross-sectional regression are averaged over time, so there is no time variation, although a rolling (time-varying) beta approach in the first stage time-series estimation is used. Most previous papers on asset pricing have also used this "unconditional" approach.

However, not only the liquidity betas, but also the liquidity premium or investor aversion to risk could exhibit time-variation. The premium might be extremely high during stress periods and negligible during normal times. That would explain why we do not see a significant economic impact of liquidity risk from unconditional models when the liquidity impacts are averaged across periods.

In order to take a preliminary look at whether liquidity risk premia are time-varying, we divide the whole sample into five three-year sub-periods (1994–96, 1997–99, 2000–02, 2003–05 and 2006–09) and re-estimate model 5.3 in Table 3-5. Figure 3-2 shows the liquidity risk premium estimated from a cross-section regression for each sub-period. The results indicate that the liquidity risk premium varies quite markedly over time. All estimates are significant, except that for the 2006–2009 period. The global price of liquidity risk (or investors' risk aversion toward liquidity comovement) seems to relate to general economic conditions as it is higher (more negative value) after the 1997–99 period of Asian, Russia and LTCM crises. Therefore, in this section, we turn our attention to conditional liquidity risk.

Figure 3-2: Liquidity risk premia in sub-periods

This figure shows liquidity premia estimated from five three-year sub-periods (1994–96, 1997–99, 2000–02, 2003–05 and 2006–09) using the cross-sectional regression equation of model 5.3 in Table 3-5. However, because of data availability, we employ the entire sub-period sample rather than rolling window approach in the time-series beta estimation for each sub-period. t-statistics from Newey West (1987) are reported in the parentheses and the significance level is labeled by [a], [b]and [c] for 10%, 5% and 1% respectively.



3.5.1 Regime-switching model of bond betas (time-series)

The model creates two regression equations relating the bond returns to relevant risk factors for each regime. We allow all betas to be potentially different between two regimes. The general hypothesis is that liquidity risks vary across two different states of the world, with the states determined by the switching function. We use the model of Goldfeld and Quandt (1973), in which the return observations are sorted by a linear switching (or constraint) function whose parameters are not known. The switching function sets up a boundary, as it were, between the two regimes. In their studies of time-varying liquidity betas, Watanabe and Watanabe (2008) and Acharya, Amihud and Bharath (2010) employ the Markov regime-switching model of Hamilton (1994), where the probabilities of state transition are assumed to be constant rather than varying with some exogenous variables. For instance, the asset returns might be subject to the random shifts without any economic interpretation. However, in our model, we relate the switching probability to underlying economic conditions as proxied by U.S. equity-market returns. For more detail about the Goldfeld and Quandt regime-switching employed here, please see Appendix B.

The two regimes with constraints are given by

$$\begin{aligned}
&r^i_{S_t=1} - r^f_t = \alpha^i_{S_t=1} + \beta^{ILLIQ,i}_{S_t=1} ILLIQ_t + \beta^{DEF,i}_{S_t=1} DEF_t + \beta^{TERM,i}_{S_t=1} TERM_t + \varepsilon^i_{S_t=1},\\
&\text{if } p^{US}(R^{USEQ_MKT}_t - R^{USEQ_MKT}_{t-1}) \le 0 \text{ and}\\
&r^i_{S_t=2} - r^f_t = \alpha^i_{S_t=2} + \beta^{ILLIQ,i}_{S_t=2} ILLIQ_t + \beta^{DEF,i}_{S_t=2} DEF_t + \beta^{TERM,i}_{S_t=2} TERM_t + \varepsilon^i_{S_t=2},\\
&\text{if } p^{US}(R^{USEQ_MKT}_t - R^{USEQ_MKT}_{t-1}) > 0,
\end{aligned} \tag{3.8}$$

where the r^i_t is the monthly return in U.S. dollar on bond portfolio i at time t, r^f is the monthly return for holding one-month U.S. Treasury bills, *ILLIQ* (the innovation in bond market illiquidity as computed in Section 3.3.3) serves as the market liquidity factor, R^{USEQ_MKT} is the monthly return on the U.S. equity market, $s_t = 1, 2$ represents the regimes and the other notations are the same as in Equation (3.5). α_1^i, a_2^i, β_1, β_2, p^{US} (scaling parameter), σ_1^i and σ_2^i (the standard deviation of residuals from Equation (3.8)) are parameters to be estimated by the maximum likelihood method. Our null hypothesis is that the regimes do not make any difference among the $t = 1,\ldots,T$ portfolio return observations, i.e., that betas or return sensitivity to factors are not time-varying and are not significantly different between regimes. The likelihood ratio (LR) method is applied to test this hypothesis.

The residual vector in Equation (3.8) is of the following form:

$$\varepsilon_t^i \left| s_t \right. = \begin{bmatrix} \varepsilon_{S_t=1}^i \\ \varepsilon_{S_t=2}^i \end{bmatrix} \sim N(0,\Omega),$$
$$\Omega = \begin{bmatrix} \sigma_{S_t=1}^2 & 0 \\ 0 & \sigma_{S_t=2}^2 \end{bmatrix}. \quad (3.9)$$

This means that the residual is assumed to follow a bivariate Gaussian process with a state-dependent variance-covariance matrix. We allow the residuals to be heteroscedastic among the two states, but assume that their covariance is zero for the sake of estimation.

We relate the change in regime to the monthly change in U.S. equity market returns, leading to a switching function of the form, $p^{US}(R_t^{USEQ\_MKT} - R_{t-1}^{USEQ\_MKT})$.[72] We use U.S. equity returns because: 1) we are looking from the U.S. investor's point of view, so the performance of the U.S. equity market should be highly relevant since it is a large part of their whole portfolio;[73] 2) U.S. equity market performance is positively related to global economic conditions and global economic sentiments; and 3) our empirical results in Section 3.4.4 indicate that the U.S. equity market has an influence on international bond prices. The bad state (or high preference uncertainty or low degrees of market optimism) occurs when $(R_t^{USEQ\_MKT} - R_{t-1}^{USEQ\_MKT}) \leq 0$ and the normal state (or low preference uncertainty or high degree of market optimism) occurs when $(R_t^{USEQ\_MKT} - R_{t-1}^{USEQ\_MKT}) > 0$. The bad and good states are denoted as Regime 1 and Regime 2 respectively. Later, as a robustness test, we will repeat the same analysis

[72] The results reported below are still the same when we use the quarterly performance of U.S. equity market, i.e., $p^{US}[(R_t^{USEQ\_MKT} + R_{t-1}^{USEQ\_MKT} + R_{t-2}^{USEQ\_MKT}) - (R_{t-3}^{USEQ\_MKT} + R_{t-4}^{USEQ\_MKT} + R_{t-5}^{USEQ\_MKT})]$, rather than the monthly performance.

[73] For example, a flight out of equities will lead to a flight onto bond markets when the risk in equity market increases (Connolly, Stivers and Sun (2005)).

using the change in aggregate bond market volatilities as another switching function because this factor is also important for bond returns from the unconditional regression in Section 3.4.4.

3.5.1.1 Regime-switching results

Our main objective is to discover whether liquidity betas are time-varying, i.e., liquidity betas are significantly different between the two regimes. We separate individual bonds into two groups according to the level of market development because we expect to find that less-developed countries exhibit higher liquidity-risk betas than developed countries and they should become even larger in a downturn.[74] This conjecture is supported by the findings of Karolyi, Lee and Dijk (2009), where stocks in emerging countries show higher level of commonality in liquidity (i.e., liquidity risk) than those in developed nations.

Table 3-8 reports the estimated parameters of the regime-switching model of Equation (3.8). The table is divided into two columns representing the two bond portfolios (i.e., developed GBI and emerging EM bond portfolios), which are estimated separately. The two sub-columns for each bond portfolio represent the results for Regimes 1 and 2 respectively. The estimation is done by maximum likelihood, using a monthly sample from December 1989 to February 2009.[75]

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[74] The results in Appendix A suggest that liquidity risk is relatively more important in less-advanced countries. Such grouping is also for parsimony of estimated econometric models. The list of GBI and EM countries can be seen in Appendix A.

[75] It should be noted that the number of observations included for the EM bond portfolio is less than that for the GBI bond portfolio because its data is available from February 2002 onwards.

Table 3-8: Regime-switching regression (time-series) with U.S. equity returns

This table shows estimated parameters of the following bivariate regime-switching model:

$$r^i_{S_t=1} - r^f_t = \alpha^i_{S_t=1} + \beta^{ILLIQ,i}_{S_t=1} ILLIQ_t + \beta^{DEF,i}_{S_t=1} DEF_t + \beta^{TERM,i}_{S_t=1} TERM_t, \text{if } p^{US}(R^{USEQ\_MKT}_t - R^{USEQ\_MKT}_{t-1}) \le 0,$$

$$r^i_{S_t=2} - r^f_t = \alpha^i_{S_t=2} + \beta^{ILLIQ,i}_{S_t=2} ILLIQ_t + \beta^{DEF,i}_{S_t=2} DEF_t + \beta^{TERM,i}_{S_t=2} TERM_t, \text{if } p^{US}(R^{USEQ\_MKT}_t - R^{USEQ\_MKT}_{t-1}) > 0,$$

where the r^i_t is the monthly return in U.S. dollar on bond portfolio *i* at time t, r^f is the monthly return for holding one-month U.S. Treasury bill, *ILLIQ* or the innovation in bond market illiquidity as computed in Section 3.3.3 serves as a liquidity factor, *DEF* is the difference between value-weighted monthly return on all non-investment grade bonds with at least ten years to maturity and that of all investment grade bonds, *TERM* is the difference between the monthly government bond return on a value-weighted portfolio of all bonds with at least ten years to maturity and the monthly one-month U.S. Treasury-bill return, R^{USEQ_MKT} is the monthly return on the U.S. equity market, p^{US} is the switching function parameter and s_t = 1, 2 represents the regimes. We sort portfolio *i* into 2 groups, GBI and EM. The estimation is done by the maximum likelihood method. t-statistics are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively. σ_1^i and σ_2^i are the standard deviation of residuals corresponding to states 1 and 2 respectively. The table also shows the likelihood ratio (LR) test on various parameters restrictions. The LR tests give the probability of being greater than the relevant χ^2 value (or the lowest significance level at which a null hypothesis can be rejected). The data start from December 1985 to February 2009.

	GBI (developed)		EM (emerging)	
	Regime 1	Regime 2	Regime 1	Regime 2
Constant (α)	1.859 [b]	-0.171	5.146	1.611
	(2.52)	-(0.22)	(1.05)	(0.34)
ILLIQ	-26.827	8.531	-88.699 [b]	5.603
	-(1.25)	(0.70)	-(2.36)	(0.08)
DEF	0.043	-0.029	0.346 [b]	0.288 [a]
	(1.37)	-(0.83)	(2.19)	(1.96)
TERM	0.709 [c]	0.686 [c]	1.195 [c]	0.364
	(11.44)	(10.44)	(5.77)	(1.58)
σ_{St}	1.037 [c]	1.159 [c]	2.705 [c]	2.649 [c]
	(7.95)	(7.49)	(7.34)	(7.21)
p^{US}	0.110		0.181 [b]	
	(1.46)		(2.17)	
Number of observations	160		85	
R^2	0.812		0.577	
Adjusted R^2	0.779		0.520	
LR test: Pr > χ^2				
$\alpha_1 = \alpha_2$	0.037		0.687	
$\beta_1^{ILLIQ} = \beta_2^{ILLIQ}$	0.074		0.023	
$\beta_1^{DEF} = \beta_2^{DEF}$	0.192		0.830	
$\beta_1^{TERM} = \beta_2^{TERM}$	0.840		0.009	
$\sigma_{St=1} = \sigma_{St=2}$	0.551		0.917	

We find that the liquidity betas or the estimated coefficients on the innovation in bond market illiquidity (*ILLIQ*) of the two portfolios vary significantly across the two regimes. The likelihood ratio (LR) test in the bottom panel of the table shows that liquidity betas for Regime 1 are significantly more negative than those for Regime 2 for both GBI and EM bonds. The null hypothesis that $\beta^{ILLIQ}{}_1 = \beta^{ILLIQ}{}_2$ is rejected with *p*-value below 0.074 for GBI bonds and 0.023 for EM bonds. The more negative (and significant) liquidity beta in Regime 1 for the EM bond portfolio suggests that the global liquidity factor is more important for countries with less-developed bond markets during times of stress. Note that the magnitude of liquidity risk is greater for EM bonds than that for GBI bonds for each regime, but this difference is significant only in bad times (Regime 1).

Turning to the other variables, the *DEF* betas are not significantly different across regimes according to the LR test. They are significantly positive only for the EM bond portfolio in both regimes and, as expected, higher in Regime 1 (the bad state). The TERM betas are positive as expected and statistically different across regimes for the EM bonds, but not for the GBI bonds.

The estimated bond volatilities (σ_{St}) are all positive and highly significant. As expected, the volatilities of the EM bond portfolio are significantly higher than those of the GBI portfolio in both regimes.[76] However, the LR tests at the bottom the table cannot reject the null hypothesis that $\sigma_{st=1}{}^{i} = \sigma_{st=2}{}^{i}$ for i = GBI, EM. The volatilities therefore vary

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[76] The hypothesis tests that H_0: $\sigma_{st=1}{}^{EM} \leq 1.037$ and H_0: $\sigma_{st=2}{}^{EM} \leq 1.159$ are both strongly rejected or Prob ($\hat{\sigma}_{st=1}{}^{EM} \geq 1.037+$ [$t_{0.01}$ * (standard error of $\hat{\sigma}_{st=1}{}^{EM}$)]) = 0.99 and Prob ($\hat{\sigma}_{st=2}{}^{EM} \geq 1.159+$ [$t_{0.01}$ * (standard error of $\hat{\sigma}_{st=2}{}^{EM}$)]) = 0.99. And the same results apply for H_0: $\sigma_{st=1}{}^{GBI} \geq 2.705$ and H_0: $\sigma_{st=2}{}^{GBI} \geq 2.649$.

across bond asset classes, but not across time in our sample. The estimated scaling parameter, p^{US}, suggests that if U.S. market returns drop by one standard deviation, probability of being in bad states is about 40% (44%) for GBI (EM) bonds.

Panel A of Figure 3-3 plots the time series of the indicator variable, where it equals to one if the probability of being in Regime 1 is greater than 0.9, using results from the regression in Table 3-8 for EM bonds. An increase in the probability of being in Regime 1 coincides with global economic crises such as the U.S. stock market crash of October 1987, the Iraq war of August 1990, the Asian Crisis of mid 1997, the Russian currency devaluation of August 1998, the LTCM crisis of September 1998, the Post Dot Com bubble burst of 2000–02 and the most recent credit crunch of 2008. Panel B of Figure 3-3 shows that similar results are obtained if a cut-off probability of 0.8 is used instead of 0.9. Both figures are consistent with the plot of innovations in aggregate illiquidity costs or liquidity shocks given earlier in Figure 3-1.

We have also experimented with different portfolios including individual country bond portfolio, region (Asia, Europe and Latin America) portfolio and G5-country portfolio. The results of time-varying liquidity betas are similar to those already reported.

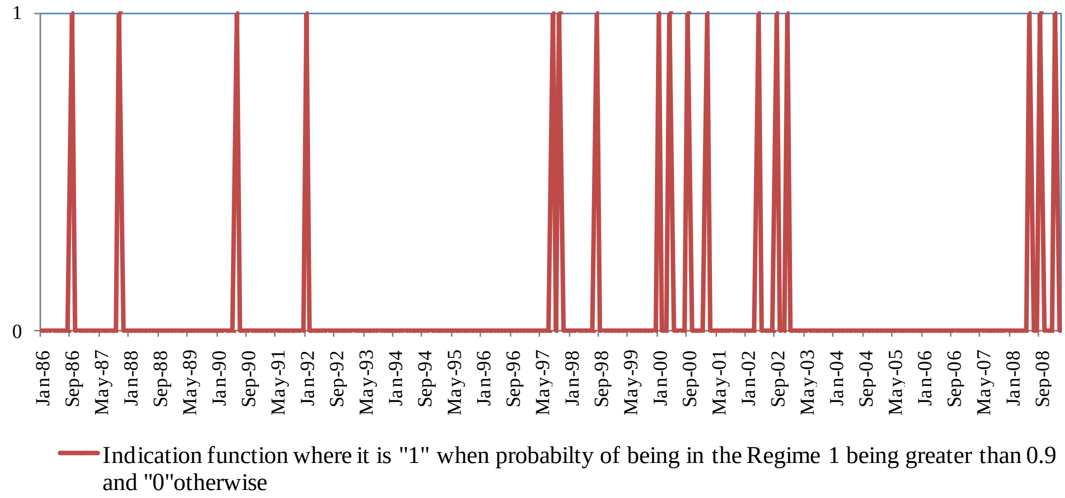
3.5.1.2 Economic significance

The economic significance of the conditional liquidity risk reported in Table 3-8 is also stronger during bad times (Regime 1) for both GBI and EM bonds. Table 3-9 shows how much of a standard deviation in returns is related to a standard deviation shock in a risk factor. During bad times, one standard deviation increase in liquidity risk factor is associated with 28 per cent (49 per cent) of one standard deviation shock in GBI bonds

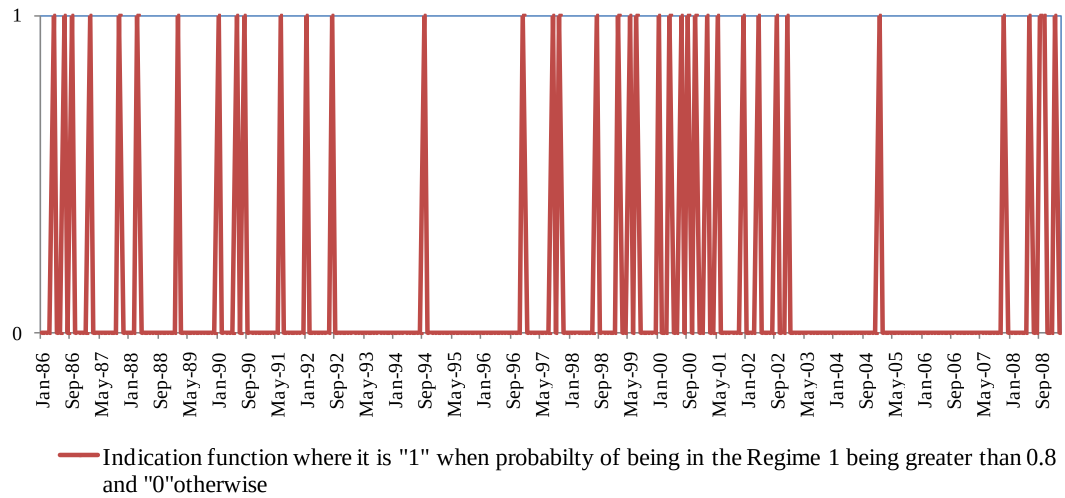
Figure 3-3: Indicator variable of high illiquidity regime (Regime 1) from a regime-switching model

Panel A (Panel B) plots the time-series of an indicator variable, where it depicts "1" when the probability of being in Regime 1 is greater than 0.9 (0.8) and "0" otherwise. The probability of being in Regime 1 is calculated by parameters estimated from the regime-switching regression of EM bonds in Table 3-8.

Panel A: with probability threshold of 0.9



Panel B: with probability threshold of 0.8



(EM bonds) returns, which is 2.80 times (12.25 times) as large as those during normal times. In terms of returns, one standard deviation in liquidity shock generates the return change of 6.72 and 13.12 per cent per annum for GBI and EM bonds respectively, which are quite large. Clearly, the time-varying liquidity effect is considerably stronger for EM bonds. Meanwhile, the *DEF* effect seems to be relatively stable for both GBI and EM bonds. As expected, its effect is more important for EM bonds, which feature lower credit ratings. Hence, they are more sensitive to an aggregate credit quality shock. The *TERM* effect is also stable for GBI bonds, while it is more volatile for EM bonds, where it increases by 2.48 times in bad times. Consistent with Beber, Brandt and Kavajecz (2009), for Euro bonds, the liquidity effect plays a substantially smaller role during the normal or unconditional times and increases significantly during times of heighten market uncertainty.

Table 3-9: Economic significance of estimated coefficients in the regime switching model

This table reports the economic significance of estimated coefficient in the regime switching model from Table 3-8. r^{GBI} and r^{EM} are the monthly return in U.S. dollar on bond portfolio of GBI and EM respectively. *ILLIQ* or the innovation in bond market illiquidity as computed in Section 3.3.3 serves as a liquidity factor, *DEF* is the difference between value-weighted monthly return on all non-investment grade bonds with at least ten years to maturity and that of all investment grade bonds. *TERM* is the difference between the monthly government bond return on a value-weighted portfolio of all bonds with at least ten years to maturity and the monthly one-month U.S. Treasury-bill return. s_t = 1, 2 represents the regimes (stress and normal times). The data start from December 1985 to February 2009.

	Bad time: Regime 1 ($s_{t=1}$)			Normal time: Regime 2 ($s_{t=2}$)		
	coefficient	σ	coeff·$\sigma_{factor} \div \sigma_{return}$	coefficient	σ	coeff·$\sigma_{factor} \div \sigma_{return}$
GBI return (r^{GBI})		2.00			1.86	
ILLIQ	-26.83	0.02	28%	8.53	0.02	10%
DEF	0.04	4.89	10%	-0.03	5.35	8%
TERM	0.71	2.60	92%	0.69	2.47	91%
EM return (r^{EM})		3.77			2.76	
ILLIQ	-88.70	0.02	49%	5.60	0.02	4%
DEF	0.35	4.89	45%	0.29	5.35	56%
TERM	1.20	2.60	82%	0.36	2.47	33%

In summary, return sensitivity to global liquidity factor for domestic bonds around the world exhibits a time-varying component (i.e., is subject to a change in regime). In addition, liquidity betas of emerging countries are more sensitive to regime changes than those of developed countries because the difference in illiquidity betas between the two regimes ($\beta^{ILLIQ}_1 - \beta^{ILLIQ}_2$) is greater for the EM bond portfolio. We find that a liquidity factor is more important 1) for a country, where the bond market is not fully mature and 2) during times of stress related to bad U.S. equity market performance.

3.5.1.3 Robustness test

If the international bond markets are segmented from the U.S. equity market, then using aggregate bond volatility as the switching function might be more appropriate. The results in Section 3.4.4 support that volatility is important for bond pricing. In addition, Chordia, Roll and Subrahmanaym (2000) and Acharya and Pedersen (2005) argue that volatility within a market causes that market to value liquidity relatively more because the changes in market volatility affect systematic liquidity by creating correlated patterns among investors and affect the supply of liquidity by market makers. Therefore, we test this with a new constraint function, given by $p^{VOL} - VOL_t$, where VOL_t is the aggregate bond market volatility and p^{VOL} is a scaling parameter to be estimated. We are likely in the Regime 1 (bear market) when the market volatility is greater than an estimated threshold level p^{VOL}. The test hypothesis remains that liquidity beta is time-varying and increases in the state of relatively high volatility (or high uncertainty). With this constraint function, we can estimate the parameter p^{VOL}, which represents the maximum volatility level before the transition from the low to high liquidity risk state. The two regimes with the new constraints are therefore given by

$$\begin{aligned} r^i_{S_t=1} - r^f_t &= \alpha^i_{S_t=1} + \beta^{ILLIQ,i}_{S_t=1} ILLIQ_t + \beta^{DEF,i}_{S_t=1} DEF_t + \beta^{TERM,i}_{S_t=1} TERM_t + \varepsilon^i_{S_t=1}, \text{if } p^{VOL} - VOL_t \leq 0, \\ r^i_{S_t=2} - r^f_t &= \alpha^i_{S_t=2} + \beta^{ILLIQ,i}_{S_t=2} ILLIQ_t + \beta^{DEF,i}_{S_t=2} DEF_t + \beta^{TERM,i}_{S_t=2} TERM_t + \varepsilon^i_{S_t=2}, \text{if } p^{VOL} - VOL_t > 0. \end{aligned} \quad (3.10)$$

Table 3-10 reports the results from estimating Equation (3.10). In general, the results are consistent with those in Table 3-8, in the sense that liquidity beta is significant and higher in Regime 1 for the EM bond portfolio. Liquidity risk remains significantly

Table 3-10: Regime-switching regression (time-series) with changes in bond volatility

This table shows estimated parameters of the following bivariate regime-switching model:

$$r^i_{S_t=1} - r^f_t = \alpha^i_{S_t=1} + \beta^{ILLIQ,i}_{S_t=1} ILLIQ_t + \beta^{DEF,i}_{S_t=1} DEF_t + \beta^{TERM,i}_{S_t=1} TERM_t, \text{ if } p^{VOL} - VOL_t \le 0,$$

$$r^i_{S_t=2} - r^f_t = \alpha^i_{S_t=2} + \beta^{ILLIQ,i}_{S_t=2} ILLIQ_t + \beta^{DEF,i}_{S_t=2} DEF_t + \beta^{TERM,i}_{S_t=2} TERM_t, \text{ if } p^{VOL} - VOL_t > 0,$$

where the r^i_t is the monthly return in U.S. dollar on bond portfolio i at time t, r^f is the monthly return for holding one-month U.S. Treasury bill, *ILLIQ* or the innovation in bond market illiquidity as computed in Section 3.3.3 serves as a liquidity factor, *DEF* is the difference between value-weighted monthly return on all non-investment grade bonds with at least ten years to maturity and that of all investment grade bonds, *TERM* is the difference between the monthly government bond return on a value-weighted portfolio of all bonds with at least ten years to maturity and the monthly one-month U.S. Treasury-bill returns, VOL_t is the aggregate bond market volatility, p^{VOL} is the switching function parameter, and s_t = 1, 2 represents the regimes. We sort portfolio i into 2 groups, GBI and EM. The estimation is done by the maximum likelihood method. t-statistics are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively. σ_1^i and σ_2^i are the standard deviation of residuals corresponding to states 1 and 2 respectively. The table also shows the likelihood ratio (LR) test on various parameters restrictions. The LR tests give the probability of being greater than the relevant χ^2 value (or the lowest significance level at which a null hypothesis can be rejected). The data start from December 1985 to February 2009.

	GBI (developed)		EM (emerging)	
	Regime 1	Regime 2	Regime 1	Regime 2
Constant (α)	1.116	0.838 [a]	10.332 [a]	-32.476
	(0.05)	(1.91)	(1.92)	-(0.89)
ILLIQ	10.711	-9.313	-147.281 [a]	514.708
	(0.04)	-(1.56)	-(1.89)	(0.89)
DEF	0.569	-0.010	0.216	1.407 [a]
	(0.53)	-(0.53)	(1.55)	(1.79)
TERM	0.790	0.680 [c]	0.751 [c]	1.999 [a]
	(1.55)	(16.60)	(4.75)	(1.94)
σ_{St}	0.311	0.880 [c]	2.839 [c]	1.927 [c]
	(0.04)	(12.64)	(5.69)	(5.72)
p^{VOL}	4.121[b]		1.176[b]	
	(3.88)		(2.41)	
Number of observations	160		85	
R^2	0.807		0.525	
Adjusted R^2	0.794		0.468	
LR test: Pr > χ^2				
$\alpha_1 = \alpha_2$	0.735		0.009	
$\beta_1^{ILLIQ} = \beta_2^{ILLIQ}$	0.911		0.003	
$\beta_1^{DEF} = \beta_2^{DEF}$	0.222		0.051	
$\beta_1^{TERM} = \beta_2^{TERM}$	0.883		0.157	
$\sigma_{St=1} = \sigma_{St=2}$	0.966		0.375	

different across regimes for the EM bond portfolio, but not for the GBI bond portfolio. The volatility threshold level (p^{VOL}) for regime switching is 4.12% and 1.18% per month (or 14.28% and 4.07% per annum) for the GBI and EM bond portfolios respectively.[77] This implies that the GBI bond portfolio is much more resilient to an increase in the market volatility or the shock in market return, i.e., the aggregate market volatility has to reach 14.28% per annum to justify the switch from a normal to bad state. Meanwhile, it is only 4.07% per annum for EM bonds. This also means that emerging bond markets experience a high liquidity risk state more often than their more developed counterparts.

3.5.2 Estimation of conditional liquidity risk premium

In this section, following the approach of Watanabe and Watanabe (2008), we test whether the liquidity risk premium varies across the two liquidity-beta states. From the cross-section pricing model in Equation (3.6),

$$E(r_t^i - r_t^f) = \phi + \lambda^{DEF}\hat{\beta}^{DEF,i} + \lambda^{TERM}\hat{\beta}^{TERM,i} + \lambda^{ILLIQ}\hat{\beta}^{ILLIQ,i} + \eta^i .$$

If we allow the liquidity betas to vary discontinuously across two states, we can define a conditional liquidity factor as

$$CILLIQ_t = I_t \cdot ILLIQ_t , \tag{3.11}$$

[77] The average aggregate market volatility ranges within 5-6% per annum historically.

where I_t is an indicator variable that takes a value of 1 if the estimated probability of being in Regime 1 (stress state) is higher than 0.9 in month t.[78] Month t is in high liquidity beta state if $I_t = 1$. The indicator variable is computed as in Section 3.5.1.1 and plotted in Figure 3-3. We test the role of the conditional liquidity factor, $CILLIQ_t$, by once again using the 2-stage Fama-MacBeth (1973) estimation. The 1st stage time-series and 2nd stage cross-section estimations are respectively

$$\begin{aligned} r_t^i - r_t^f &= \alpha^i + \beta^{DEF,i} DEF_t + \beta^{TERM,i} TERM_t + \beta^{ILLIQ,i} ILLIQ_t + \beta^{CILLIQ,i} I_t \cdot ILLIQ_t + \varepsilon_t^i, \\ E(r_t^i - r_t^f) &= \phi + \lambda^{DEF} \hat{\beta}^{DEF,i} + \lambda^{TERM} \hat{\beta}^{TERM,i} + \lambda^{ILLIQ} \hat{\beta}^{ILLIQ,i} + \lambda^{CILLIQ} \hat{\beta}^{CILLIQ,i} + \eta_t^i, \end{aligned} \tag{3.12}$$

where $\beta^{CILLIQ,i}$ is the time variation in the liquidity beta or conditional beta. Aggregate liquidity beta equals $\beta^{ILLIQ,i}$ + $\beta^{CILLIQ,i}$ in Regime 1 (stress state) and switches to just $\beta^{ILLIQ,i}$ in Regime 2 (normal state). The other notations are the same as Equations (3.5) and (3.6). In the two-stage estimation, the entire sample is, however, employed in the time-series beta estimation because the liquidity beta is time-varying by the indicator rather than by the rolling estimation. We set the probability threshold of being in Regime 1, which is used to compute the indicator variable, to be either 0.9 or 0.8.[79] We expect to see a significantly negative premium on conditional liquidity risk, $\beta^{CILLIQ,i}$, if the price of liquidity risk is greater during periods of higher risk.

Table 3-11 reports the results from cross-sectional regressions for country bond portfolios.[80] It shows that including the conditional liquidity betas does not change the

[78] This is the probability that Probability (S_t = 1 | Ω_{t-1}) > 0.90, where Ω_{t-1} is the all information available at time t–1.

[79] The probability threshold of 0.6 or 0.7 also gives similar conclusions.

[80] We do not include the illiquidity cost in Table 3-11 since it does not change the results.

Table 3-11: Country portfolios and Fama-MacBeth regression with conditional liquidity factor (cross-section)

This table reports the time-series averages of coefficients of each beta obtained in a cross-sectional regression. A two-step Fama-Macbeth (1973) procedure is employed. First, estimates of the systematic risk (betas) are obtained by running a regression of bond's monthly returns, r^i_t on different risk factors. The models are alternative cases of the following equation:

$$r_t^i - r_t^f = \alpha^i + DEF_t\beta^{DEF,i} DEF_t + \beta^{TERM,i} TERM_t + \beta^{MKT,i}(r_t^{MKT} - r_t^f) + \beta^{ILLIQ,i} ILLIQ_t + \beta^{CILLIQ,i} \cdot I_t \cdot ILLIQ_t,$$

where α^i is the intercept, r^f_t is the risk-free rate, $\beta^{DEF,i}$ is the default beta of the *i*th bond, DEF_t is the difference between value-weighted monthly return on all non-investment grade bonds with at least ten years to maturity and that of all investment grade bonds, $\beta^{TERM,i}$ is the term beta, $TERM_t$ is the difference between the monthly government bond return on a value-weighted portfolio of all bonds with at least ten years to maturity and the monthly one-month U.S. Treasury-bill return, $\beta^{MKT,i}$ is the bond market beta, r_t^{MKT} is the value-weighted bond market monthly return, $\beta^{ILLIQ,i}$ is the liquidity beta, $ILLIQ_t$ is the innovation in the market illiquidity and $I_t \cdot ILLIQ_t$ is the conditional liquidity factor, where I_t is one when the probability of being in Regime 1 is greater a specific threshold and zero otherwise. The betas are estimated using the entire sample. Our sample starts from December 1985 to February 2009.

In the second stage, expected bond returns adjusted for default loss, $E(r^i_t - r^f_t)$, are regressed on the estimated betas from Equation (3.12) in the different cross-sectional models for each month in the sample period. For each month, the cross-sectional regressions are of the following alternatives:

$$E(r_t^i - r_t^f) = \phi + \lambda^{MKT}\hat{\beta}^{MKT,i} + \lambda^{DEF}\hat{\beta}^{DEF,i} + \lambda^{TERM}\hat{\beta}^{TERM,i} + \lambda^{ILLIQ}\hat{\beta}^{ILLIQ,i} + \lambda^{CILLIQ}\hat{\beta}^{CILLIQ,i} + \eta_t^i.$$

t-statistics from Newey West (1987) are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively.

Variable	Probability of being in Regime 1 is greater 0.90		Probability of being in Regime 1 is greater 0.80	
	11.1	11.2	11.3	11.4
Intercept (ϕ)	0.092[c]	0.161[c]	0.115[c]	0.154[c]
	(4.14)	(13.92)	(6.57)	(13.23)
DEF beta ($\hat{\beta}_t^{DEF,i}$)	0.078[c]		0.051[b]	
	(2.75)		(2.19)	
TERM beta ($\hat{\beta}_t^{TERM,i}$)	0.120[c]		0.077[c]	
	(3.35)		(2.82)	
Bond market beta ($\hat{\beta}_t^{MKT,i}$)		0.011		0.010
		(0.96)		(0.90)
*Liquidity beta *100*($\hat{\beta}_t^{ILLIQ,i}$)	-0.101[c]	-0.053[c]	-0.122[c]	-0.097[c]
	-(3.73)	-(2.93)	-(4.40)	-(4.85)
*Conditional Liquidity beta *100*($\hat{\beta}_t^{CILLIQ,i}$)	-0.001	-0.001	-0.005[b]	-0.004[c]
	-(1.00)	-(1.21)	-(2.55)	-(2.75)
R^2	0.282	0.151	0.315	0.216
Adjusted R^2	0.115	0.006	0.157	0.089
Number of observations	4,588	4,588	4,588	4,588

results much relatively to those of unconditional models in Table 3-5. When we use the probability threshold of 0.9 in models 11.1 and 11.2, the liquidity risk ($\beta^{ILLIQ,i}$) is still significantly priced and the risk premium of the conditional liquidity beta ($\beta^{CILLIQ,i}$) is not significant. The *DEF* and *TERM* premia are also positive and significant in model

11.1. Again the market betas are always not significant (models 11.2 and 11.4). When we reduce the probability threshold to 0.8 in models 11.3 and 11.4, we find that the other results are still the same, except that the conditional liquidity risk premium now becomes significant for both regressions. This is due to the fact that we have more observations in bad times. The results in models 11.3 and 11.4 support our hypothesis that the liquidity risk premium is time-varying and increases during times of stress.

Observing the Argentinian and Chinese bond portfolios once again as extremes in terms of liquidity risk countries, we reported earlier in Section 3.4.3 that liquidity risk can account for 0.09% out of the 1.00% per annum of unconditional yield difference between those two country bond portfolios. Using the result in Table 3-11, model 11.3, the unconditional liquidity risk can explain a similar amount of 0.08%, whereas the conditional liquidity risk can explain another 0.04% of the unconditional yield difference between Argentinian and Chinese bond portfolios.

To summarize, we find the evidence of 1) time-varying liquidity risk for emerging-country bonds and 2) a small time-varying liquidity risk premium using a dummy for regime.[81] Our findings are consistent with conditional liquidity risk of Watanabe and Watanabe (2008) for the U.S. equity market.[82] However, the economic significance of the conditional liquidity risk premium on bond credit spreads measured here is quite stable over time.

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[81] The modest economic significance of time-varying liquidity risk premium might be because using a dummy for regime is not able to produce sufficient variation in the liquidity beta over time.

[82] Although they find that conditional liquidity risk premium is positive and significant, the risk premium for unconditional liquidity risk is negative, which is unexpected, and insignificant. Their expected signs are opposite to ours because they measure liquidity, whereas we measure illiquidity.

3.6 Conclusions

The paper examines the role of global liquidity risk in the pricing of domestic government bonds around the world. We employ both unconditional and conditional models to relate liquidity risk to bond returns. We also investigate differences between developed and emerging markets. In the unconditional version, with bond portfolios grouped by country of issuance, liquidity risk is significant in all specifications, even in the presence of individual bond characteristics and U.S equity risk factors. Investors accept lower expected returns for holding a bond that: 1) performs well when the market becomes illiquid and 2) has lower transaction costs. Since there is a spillover effect from U.S. equity market to domestic bond markets across the world, investors require a lower expected return when holding a bond that has more diversification benefit (i.e., a bond that performs well when the U.S. stock market declines or becomes more illiquid). The combined effects of liquidity risk and liquidity level in the unconditional model can explain as much as 41 basis points per annum of extra spread for the highest versus the lowest liquidity risk countries, which are China and Argentina respectively.

The conditional (regime-switching) model indicates that liquidity risk can be considerably different across regimes, particularly for government bonds issued by less-developed economies. The liquidity factor also becomes stronger in the bad state. Less-developed bond markets experience a state of high liquidity risk state much more often than developed ones. Therefore, fund managers, especially who manage emerging-country bond funds, should consider not only the level of liquidity risk, but also the abrupt change in this risk. Even though there is an evidence that periods of high liquidity risk coincide with those of high liquidity risk premia, this leads to only 4 basis points per annum of extra spread between Argentinian and Chinese government bonds. The price of conditional liquidity risk is relatively modest.

While our results suggest that global risk factors are important in pricing government bonds in both unconditional and conditional frameworks, local risk factors may be one of missing factors here since there might be a lack of ability for U.S. dollar investors to hold locally-diversified market portfolios at the country level. This conjecture of an omitted-factor problem is supported by significant positive constants or pricing errors in many specifications (both unconditional and conditional ones). Joint tests on the degree of importance of local and world factors on asset pricing could be fruitful. No study has yet investigated both local and global liquidity risk in the international bond market.[83] In addition, since there is time-variation in liquidity, further investigation of the multivariate dynamics of liquidity and its impact on asset pricing could be an important direction for future research.

[83] For the international stock markets, see Liang and Wei (2006) and Lee (2010).

Appendix 3A: Testing for the Liquidity Effect with Individual Bonds

We repeat the test in Table 3-5, but using individual bonds rather than country bond portfolios as test assets. Although the study with an individual bond will add more noise, it helps increase the test power and removes potential biases due to the sorting procedure. Before grouping the sample bonds into two groups according to their market development, it is useful to start with a regression, which uses the whole sample. Table 3A-1 below reports the Fama-MacBeth regression using all individual government bonds in the sample.

Table 3A-1: Individual bonds and Fama-MacBeth regression

Variable	A1.1	A1.2	A1.3	A1.4	A1.5	A1.6
Intercept (ϕ)	0.163[c]	0.097[c]	0.117[c]	0.071[b]	0.094[c]	0.165[c]
	(12.58)	(8.36)	(8.52)	(2.40)	(3.69)	(11.31)
Bond market beta ($\hat{\beta}_t^{MKT,i}$)	-0.003	0.093	-0.093		-0.086	-0.098[c]
	-(0.06)	(0.94)	-(1.44)		-(1.21)	-(2.62)
*Liquidity beta *100*($\hat{\beta}_t^{ILLIQ,i}$)	-0.023[b]	-0.145[c]	-0.063[a]	(0.011)	-0.077[b]	-0.026[a]
	-(2.20)	-(2.97)	-(1.72)	(0.32)	-(2.15)	-(1.71)
DEF beta ($\hat{\beta}_t^{DEF,i}$)		-0.004	-0.046	0.170	0.080	
		-(0.02)	-(0.37)	(1.49)	(0.88)	
TERM beta ($\hat{\beta}_t^{TERM,i}$)		0.286[b]	0.113[a]	-0.082	0.110[a]	
		(2.43)	(1.75)	(-1.17)	(1.72)	
Bond volatility beta ($\hat{\beta}_t^{VOL^{BOND},i}$)						-0.007[b]
						-(2.10)
Illiquidity cost (c_t^i)			0.084[b]	-(0.037)	0.103[c]	0.062[b]
			(2.44)	-(0.72)	(2.88)	(2.04)
Modified duration				0.006[c]	0.004[c]	
				(11.43)	(5.95)	
ln (*bond market value*)				0.005	-0.001	
				(0.90)	-(0.31)	
R^2	0.255	0.276	0.376	0.274	0.443	0.365
Adjusted R^2	0.221	0.245	0.335	0.243	0.410	0.308
Number of observations	36,677	38,810	31,873	30,035	30,608	29,294

Note: significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively.

The results are very similar to those in Table 3-5, both in terms of the magnitudes and signs of estimated parameters. As expected, using individual bonds adds more noise to the pricing function. This can be supported by empirical results in Table 3A-1 that the risk premium for *TERM* becomes less significant and the risk premium for the *DEF* is not significant in any regression specification, whereas that for the *TERM* risk is positive and significant except in the model A1.4, where it is negative and insignificant. Nonetheless, the liquidity risk premium and coefficient of individual bond illiquidity cost remain significant with correct signs (again except in model A1.4). Models A1.4 and A1.5 indicate that bond modified duration is highly significant, while the bond market capitalization now becomes insignificant. In the model A1.6, the bond volatility beta is again priced with correct sign. The increase in the test power can be witnessed by the improvement in adjusted R^2 in this individual bond testing (compared to the adjusted R^2 in Table 3-5).

Small and less-developed bond markets are arguably more sensitive to liquidity shocks. In order to investigate whether the liquidity factor is more important in emerging markets, we separate individual bonds in the whole sample into two country groups according to the level of bond market development (i.e., JPMorgan Government Bond Index (GBI) and JPMorgan Government Bond Index-Emerging Market (EM)) and test with the same methodology as in the Section 3.4. GBI countries are Australia, Austria, Belgium, Canada, Czech, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, Ireland, Italy, Korea, Japan, Mexico, Netherlands, New Zealand, Poland, Portugal, Singapore, Spain, South Africa, Sweden, U.K. and U.S. EM countries consist of Argentina, Brazil, Chile, China, Colombia, India, Indonesia, Malaysia, Peru, Russia, Thailand and Turkey. The list of GBI countries is almost identical to that of OECD nations, except for Hong Kong and Singapore in GBI countries. While Turkey, an OECD country, is included in EM countries. In effect, grouping bond portfolios by the degree of domestic bond market development is virtually equivalent to doing so by countries' per capita income. Table 3A-2 below shows the cross-sectional regression results for individual bonds within GBI and EM groups respectively.

Table 3A-2: Individual bonds and Fama-MacBeth regression by GBI and EM countries

Variable	GBI bonds (developed)				EM bonds (emerging)			
	A2.1	A2.2	A2.3	A2.4	A2.5	A2.6	A2.7	A2.8
Intercept (ϕ)	0.170[c]	0.123[c]	0.129[c]	0.076[b]	0.097	-0.284[b]	0.081	-0.284
	(13.26)	(5.50)	(8.74)	(2.56)	(1.59)	-(2.26)	(1.63)	-(0.77)
Bond market beta ($\hat{\beta}_t^{MKT,i}$)	-0.040	-0.085[a]			-0.762	-0.703		
	-(1.31)	-(1.79)			-(0.59)	-(0.55)		
*Liquidity beta *100*($\hat{\beta}_t^{ILLIQ,i}$)	-(0.016)	-(0.03)	0.018	0.014	-0.306[a]	-0.439[a]	-0.742	-0.645
	-(1.04)	-(1.43)	(0.60)	(0.40)	-(1.78)	-(1.70)	-(1.12)	-(0.95)
DEF beta ($\hat{\beta}_t^{DEF,i}$)			0.058	0.135			0.944	-0.388
			(0.48)	(1.16)			(0.55)	-(0.18)
TERM beta ($\hat{\beta}_t^{TERM,i}$)			-0.003	-0.085			0.479	0.979
			-(0.05)	-(1.10)			(1.41)	(1.41)
Illiquidity cost (c_t^i)	0.090[c]	0.089[c]	(0.058)	(0.068)	-(0.073)	(0.02)	-(0.085)	(0.146)
	(4.29)	(3.37)	(1.01)	(1.17)	-(0.95)	(0.31)	-(1.24)	(0.92)
Modified duration		0.004[c]		0.005[c]		0.005		0.016[a]
		(7.5)		(9.95)		(1.14)		(1.80)
ln (*bond market value*)		-0.001		0.004		0.109[c]		0.06
		-(0.30)		(0.72)		(2.89)		(0.56)
R^2	0.296	0.239	0.289	0.307	0.545	0.714	0.627	0.763
Adjusted R^2	0.256	0.210	0.255	0.276	0.279	0.478	0.379	0.544
Number of observations	29,244	27,045	28,362	27,130	2,139	2,139	2,139	2,139

Note: significance at the 10%, 5% and 1% level is indicated by [a], [b] and [c] respectively.

In Table 3A-2, liquidity risk is not priced in any specifications for GBI bonds, but it is priced for EM bonds in some specification. This is not surprising as we will see later in Tables 3-8, and 3-9 (in Section 3.5, a time-series regime-switching model) indicating that the liquidity risk factor is insignificant in both Regimes 1 and 2 for GBI bonds.

However, the illiquidity cost is positive and significant in models A2.1 and A2.2, but not significant for EM bonds. It suggests that liquidity level is more relevant than liquidity risk for bonds issued by developed economies. And the bond modified duration is in most cases positive and significant, whereas the bond market capitalization is not.

The most striking finding in Table 3A-2 is that the liquidity risk becomes relatively more important than liquidity level for bonds, which are included in EM (i.e., emerging economies). The magnitude of the liquidity risk premium for EM bonds is considerably greater than that estimated from the whole bond sample in Table 3A-1. Therefore, the economic significance of the liquidity risk premium in explaining the credit spreads is substantially higher in the case of domestic bonds issued by emerging markets rather than advanced economies.

Appendix 3B: Regime-switching by Goldfeld and Quandt (1973)

Two regimes and constraints are given by

$$y_{1t} = a_1 + b_1 x_{1t} + \varepsilon_{1t}, \text{ if } \mathrm{z}_t = \sum_{j=1}^{p} \pi_j z_{jt} \le 0$$
and
$$y_{2t} = a_2 + b_2 x_{2t} + \varepsilon_{2t}, \text{ if } \mathrm{z}_t = \sum_{j=1}^{p} \pi_j z_{jt} > 0, \tag{3B.1}$$

where y_t and x_t are dependent and independent variables, ε_t are the error terms, z_{it} are exogenous variables related to the *t-th* month's observation, π_j are unknown coefficients to be estimated (along with a_1, a_2, b_1 and b_2), and subscripts 1 and 2 represent two different regimes (say, bad and good states). z_{it} and π_j determine whether the *t-th* month's observation belongs to Regime 1 or Regime 2 in terms of probability. In other words, a constraint function z_t serves as a switching function, which is estimated by the maximum likelihood method. Introduce a unit indicator function as

$$D_t = 0 \text{ if } \sum_{j=1}^{p} \pi_j z_{jt} \le 0$$
and
$$D_t = 1 \text{ if } \sum_{j=1}^{p} \pi_j z_{jt} > 0. \tag{3B.2}$$

From the practical and statistical points of view, the above unit step function is usually replaced by a continuous cumulative normal distribution on z_t as follows:

$$d(z_t) = \frac{1}{\sqrt{2\pi\sigma}} \int_{-\infty}^{z_t} \exp\left\{ \frac{\xi^2}{2\sigma^2} \right\} d\xi, \tag{3B.3}$$

where σ is a new parameter and is estimated simultaneously with π_j. z_t is the upper boundary of the normal probability density function. If σ approaches zero, Equation (3B.3) becomes Equation (3B.2). The $d(z_t)$ forms an n-dimensional diagonal matrix $D = [d(z_t)]$. The two regressions in Equation (3B.1) can be combined with probability (I – D) and D for the respective regime in vector form as

$$Y = (I - D)XB_1 + DXB_2 + W, \tag{3B.4}$$

where $W=(I - D)U_1 + DU_2$ is the vector of unobservable and heteroscedastic error terms. The variance-covariance matrix of W is given by

$$\Omega = (I - D)^2\sigma_1^2 + D^2\sigma_2^2. \tag{3B.5}$$

The covariance between ε_{1t} and ε_{2t} is assumed to be zero for the sake of estimation. The maximum likelihood parameters to be estimated are a_1, a_2, b_1, b_2, π_j, σ_1 and σ_2 by maximizing the following log-likelihood function:

$$\begin{aligned}\log L = &-\frac{T}{2}\log 2\pi - \frac{1}{2}\log|\Omega| \\ &-\frac{1}{2}\left\{\left[Y-(I-D)XB_1 - DXB_2\right]'\,\Omega^{-1}\left[Y-(I-D)XB_1 - DXB_2\right]\right\}.\end{aligned} \tag{3B.6}$$

The hypothesis is that each regime will have its own different regression function. The likelihood ratio (LR) method is applied to test such hypothesis. More specifically, the null hypothesis is that the regimes do not make any difference among the $t = 1,\ldots,T$ portfolio return observations.

CHAPTER 4

LIQUIDITY SPILLOVERS:

THEORY AND EVIDENCE FROM EMERGING BOND MARKETS

Abstract

We examine whether liquidity spillovers between sovereign bonds are systematic or idiosyncratic in character. A theoretical model is developed, which demonstrates that idiosyncratic spillovers require returns to be correlated, whereas systematic spillovers require volatilities to be correlated. We apply the model to sovereign bonds in 35 emerging markets, aggregated for some analyses into Asian, European and Latin American regions. We find liquidity spillovers mainly from Latin America to the other regions and they are both systematic and idiosyncratic in character. Further cross-sectional analysis (by country) and time-series analysis (by region) show that systematic spillovers are more important than idiosyncratic spillovers. The conclusion is that most liquidity risk across emerging bond markets is systematic and therefore cannot easily be hedged away. This has important implications for portfolio selection by fund managers and for the regulation of systemic risk.

4.1 Introduction

Most studies of liquidity have assumed that it is exogenously determined, i.e., without having an explicit causal mechanism. In this paper, we address the fundamental questions of what lies behind liquidity risk and what drives liquidity spillovers across financial markets beyond national boundaries.[84] In previous two chapters, we find that liquidity risk is important and priced in both U.S. dollar-denominated sovereign bonds issued by emerging countries and domestic-currency government bonds issued by both developed and developing nations. In this paper, we take a step back and investigate more closely why there is liquidity risk or liquidity co-movement in the first place.

The paper addresses both theoretical and empirical questions of what are the fundamental determinants of liquidity commonality. Building on Fernando (2003), we develop a model for two assets with correlated returns. Liquidity shocks are defined as changes in an asset's value that are not caused by fundamentals. Such shocks can be decomposed into two components, systematic and idiosyncratic: systematic shocks are common across all investors, whereas idiosyncratic shocks affect individual investors differently. Our model suggests that these two components are related to different types

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[84] According to Acharya and Pedersen (2005), liquidity risk is defined as liquidity co-movement with the market factors and it can be decomposed into three components, 1) commonality in individual asset's liquidity and market-wide liquidity or Cov(c^i,c^M), 2) return loading on aggregate liquidity or Cov(r^i,c^M) and 3) co-movement between market return and individual asset's liquidity or Cov(c^i,r^M), where r^i (c^i) is the return (illiquidity cost) of security *i* and r^M (c^M) are the market return (market illiquidity cost). As suggested by the first research paper in Chapter 2, all three liquidity risks are highly correlated. In this paper, we therefore focus our interest on the first component of the liquidity risk, which is the same liquidity risk as studies in Chordia, Roll and Subrahmanyam (2000), Hasbrouck and Seppi (2000) and Huberman and Halka (2001). Throughout the paper, the term "liquidity spillovers" is referred to the cross-autocorrelation of liquidity across markets. We sometimes replace this term with "liquidity transmission", "commonality in liquidity" and "contagion in liquidity.

of liquidity contagion and they have different effects on asset prices, trading volumes and volatilities.

A systematic liquidity shock affects all bonds and investors equally and there is therefore no incentive for investors to buy or sell any particular bond in response to such a shock: relative bond prices do not change. At the same time, any bond transactions, which occur, will face larger bid/ask spreads, so all bond volatilities will rise. A systematic liquidity shocks is therefore associated with an increase in the second moment of log bond prices (volatility), but no change in the first moment of log relative bond prices (returns).

An idiosyncratic liquidity shock is one which, by definition, applies to one bond (or group of bonds), but not to any other bonds. The response of investors to such a shock would be to try to sell the affected bond, but this is made difficult by the shock, which has occurred to the liquidity of that bond. Investors therefore prefer to sell a close-substitute (correlated-return) bond, i.e., one which has not been directly affected by the reduction in liquidity, but which behaves similarly to the bond in question. An idiosyncratic liquidity shock is therefore associated with a change in the first moment of log bond prices (returns) for a subset of related bonds, but has no general impact on the second moment of log bond prices (volatility). It follows that an idiosyncratic shock can only induce commonality in liquidity if asset returns are mutually related

We apply the model to a sample of U.S. dollar sovereign bonds issued by 35 emerging countries, which runs daily from December 1993 to January 2010. There have been several previous studies on liquidity commonality, which focus on one particular country, in most cases, the U.S. stock market. Fortunately with this set of data, we are able to investigate liquidity spillovers for a large number of countries without the need to concern on exchange rate movements. The empirical analysis is divided into two parts. In the first, a vector autoregression (VAR) is used to track liquidity, return and volatility spillovers and in the second, "commonality" measure is estimated for liquidity, returns and volatility for each country and region, which is then used as a dependent variable in a further regression to explain whether systematic or idiosyncratic liquidity spillovers are more important.

In the first part, using the VAR approach, we find that there is a consistent pattern of spillovers in liquidity, returns and volatility from Asia to Europe and from Latin America to both Asia and Europe. Both systematic and idiosyncratic liquidity shocks are found to be relevant in explaining liquidity transmission across regions.

In the second part, both cross-section and time-series analyses find that commonality in liquidity is more closely associated with commonality in volatility than with commonality in returns. It follows that systematic shocks are more statistically and economically significant than idiosyncratic shocks in explaining liquidity transmission, both across countries (at one time) and across regions (over time). We also find that commonality in liquidity varies considerably over time and increases sharply during periods of global financial crisis.

The implication is that most liquidity risk across emerging-market bonds is systematic and cannot easily be diversified away. This is an important finding for fund managers and regulators of financial markets because it implies that the benefits of emerging market portfolio diversification, which are based on low return correlations, can be swiftly cancelled out by an abrupt reduction of market liquidity (as occurred, for example, in the Asian crisis of 1997 and during the U.S. subprime crisis of 2007). Markets, which have little return correlation, may still have high liquidity commonality. Regulators need to be aware that liquidity risk in the home market is not only generated from domestic fundamentals, but also from a global liquidity factor.

The paper is organized as follows. Section 4.2 presents the related literature. The model of liquidity transmission is developed in Section 4.3. Section 4.4 gives data descriptions and their summary statistics. The empirical studies of liquidity spillovers and the relative importance of idiosyncratic and systematic shocks to liquidity are examined in Sections 4.5 and 4.6. Section 4.7 provides the conclusions of the paper.

4.2 Related Literature

The literature can conveniently be divided into theoretical and empirical parts, which will be discussed in the following two sub-sections.

4.2.1 Theoretical studies

To understand liquidity spillovers, one needs to use at least a two-asset model. However, most of the theoretical works to date have focused on the liquidity of a single asset and have not examined the liquidity transmission across assets. Many models, which relate liquidity to information asymmetry, include Kyle (1985), Admati and Pfleiderer (1988), Bhushan (1991), Chowdhry and Nanda (1991), Foster and Viswanathan (1996) and Easley, Hvidkjaer and O'Hara (2002). In general, they argue that the interplay of informed and uninformed traders influences the security's liquidity level. Another strand of the literature links liquidity to the inventory risk faced by market makers, who are forced to hold less-than-perfectly diversified portfolios (for example, Stoll (1978), Amihud and Mendelson (1980) and Grossman and Miller (1988)).

There are rather few works in a multi-asset framework. Cabelle and Krishnan (1994) show that a security's market price is not solely determined by its own order flow, but also by that of other securities because of correlated fundamentals. Baruch, Korolyi and Lemmon (2007) develop a model of multimarket trading and predict that the distribution of trading volume across exchanges is related to the correlation of cross-listed asset returns with returns of other assets traded in the respective market since high correlations enable market-makers to learn more by observing other stocks.

Our model makes a clear distinction between (i) liquidity spillovers caused by shocks, which are common (systematic) to every investor and (ii) spillovers caused by shocks, which are idiosyncratic. Some previous works also make this distinction. With respect to systematic shocks, Watanabe (2008) develops a model, where new information causes an increase in return volatility. When market makers observe an increase in the volatility of returns on liquid assets, they mark-up the trading costs of illiquid assets even more to allow for these assets' higher expected future volatility. Therefore, in this approach, liquidity spillovers co-move with volatility spillovers, but do not necessarily go together with spillovers of returns. With respect to idiosyncratic shocks, it is somewhat counterintuitive that they can lead to liquidity spillovers. This may happen if investors respond to a shock on an asset by shifting their trading to another asset with correlated returns (Fernando (2003)). Huberman and Halka (2001) make a similar argument based on shocks caused by noise traders.

4.2.2 Empirical studies

Empirical works, which study the dynamics of liquidity, include Chordia, Shivakumar and Subrahmanyam (2004), Chordia, Sarkar and Subrahmanyam (2005a), Chordia, Sarkar and Subrahmanyam (2005b), Lee (2006) and Goyenko and Ukhov (2009). Chordia et al. (2004), Chordia et al. (2005a) and Lee (2006) study liquidity dynamics across large and small U.S. stocks, using a vector autoregressive (VAR) framework. Chordia et al. (2005b) demonstrate that there are interactions among returns, volatilities and the quoted spreads for size-decile portfolios. In general, they find that innovations in stock and bond market liquidity are correlated and liquidity of small firms helps predict the future level of liquidity of large firms and vice versa. Goyenko and Ukhov (2009) show there is a lead-lag in liquidity between bond and stock markets and monetary policy shocks are reflected in bond illiquidity first. However, most empirical evidence is from U.S. financial markets and may have only limited reference to global financial markets. There is little evidence of commonality in liquidity on non-U.S. equity market; the Stock Exchange of Hong Kong by Brockman and Chung (2002) and the Australian Stock Exchange by Fabre and Frino (2004). Heretofore, the only two empirical works explore commonality in liquidity, returns and trading volume around the world. The first one is by Karolyi, Lee and Dijk (2009), who study commonality in liquidity, returns and trading volumes across 40 stock markets. They observe much greater commonality among emerging markets than among developed stock markets and more of that commonality is related to demand-side factors rather than to supply-side factors. The second one is by Brockman, Chung and Perignon (2009), who examine commonality in liquidity using data from 47 stock exchanges in 38 countries. They find that commonality in liquidity spills over the national border and individual firms are subject to both local (industry-level, exchange-level and region-level) and global (aggregate) sources of commonality. However, both studies do not explain how the three commonalities– liquidity, returns and volatility– are related to one another. This paper fills a gap in understanding the channels through which liquidity commonality in region of the world affect liquidity changes in another.

Another feature of previous studies on liquidity spillovers is a focus on stocks rather than bonds. The exception is the paper by Goyenko, Subrahmanyam and Ukhov (2008), which finds that liquidity shocks are transferred from the short end to long end of the term structure. This transmission can be related to information because short-term (more liquid and informationally-efficient) bonds absorb macroeconomic shocks first and then the shocks move into illiquidity of long-term bonds. Fontaine and Garcia (2009) find that bond liquidity co-varies with changes in aggregate uncertainty as measured by the volatility implied by S&P500 options and with changes in monetary policy as measured by bank reserves and monetary aggregates. Our empirical results are consistent with both of these previous studies, which show that liquidity spillovers can be caused by either idiosyncratic or systematic shocks.

To summarize, the theoretical literature mainly focuses on liquidity formation for a single asset. The few studies that have studied liquidity transmission across assets relate liquidity spillovers either (i) to idiosyncratic shocks (Cabelle and Krishna (1994), Fernando (2003) and Baruch et al. (2007)) or (ii) to systematic shocks (Watanabe (2008)). Our model in the next section incorporates both types of liquidity spillover. With respect to the empirical literature, in general it finds commonality in returns, liquidity and volatility especially in the U.S. financial markets. However, most studies do not investigate a basic question of what drives spillovers. Our paper is the first to investigate liquidity spillovers across international sovereign bond markets and to examine the extent to which systematic and idiosyncratic liquidity shocks cause these spillovers. In order to do so, the next section develops a model that relates return and volatility spillovers to idiosyncratic and systematic liquidity shocks.

4.3 The Model: Transmission of Returns, Trading and Liquidity

Do spillovers arise mainly because of idiosyncratic shocks or systematic shocks, or both? To motivate the discussion, consider the following two stylized examples, first of an idiosyncratic shock to liquidity and then of a systematic shock to liquidity.

In the first stylized example, the context is very approximately that which existed early in the year 2010. Let there be two cash-rich investor nations, say Germany and China, buying assets abroad. Investors in each of these two countries hold one unit of Greek sovereign bonds and one unit of Portuguese sovereign bonds, with all bonds being denominated in U.S. dollar. A liquidity shock to the Greek economy now starts to hit Greek bonds. Investors in Germany and China would like to sell Greek bonds, but illiquidity is a problem. As a result, they also sell Portuguese bonds, which are seen to be close substitutes as Greece and Portugal are considered to have similar economic fundamentals. The result is that an idiosyncratic liquidity shock to Greek bonds causes a drop in their prices and in their ex post returns, which is also transmitted to the prices and returns of Portuguese bonds. So the example suggests that idiosyncratic liquidity shocks may spill over from one country's bonds to another country's bonds if the two issuing countries (i.e., Greece and Portugal) have similar macroeconomic fundamentals and therefore have correlated bond returns.

In addition, soon the shock has an impact on the Euro/U.S.$ exchange rate, which falls, and this increases the dollar value of Greek and Portuguese bonds from a German investor's (Euro) perspective, but not from a Chinese investor's (Renminbi) perspective. The idiosyncratic liquidity shock to Greek bonds therefore has a larger negative spillover impact on returns experienced by Chinese investors than on it does on returns experienced by German investors. It also means that the impact may be felt differently across investors (Germany and China) due to exchange-rate movements.

In the second stylized example, the context is the U.S. subprime crisis, which starts in 2007. This is a worldwide systematic shock to liquidity and affects all bonds equally. So it increases the bid/ask spreads and volatilities of both Greek and Portuguese bonds. But there is no incentive for any trading by German or Chinese investors because of the generality of the impact. The systematic shock to liquidity raises bond volatilities worldwide, but does not have any differential impact across investors or induce any new trading. So the example suggests that systematic liquidity shocks may not necessarily be associated with correlated bond returns, but are always associated with correlated bond volatilities. A "blow up", such as the subprime crisis, affects the liquidity of both Greek and Portuguese bonds, but an effort by investors to avoid it by buying or selling these two countries' bonds would be completely ineffective and they would therefore not try to do so.[85]

We now develop a model, which shows more precisely how idiosyncratic liquidity shock may be associated with correlated returns and how systematic shocks may be associated with correlated volatilities. Our empirical results in Sections 4.5 and 4.6 do not entirely depend on this model because some of the model restrictions may be violated, but the model allows a clearer interpretation and intuition of those results.

4.3.1 Model setup

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[85] This is a stylized world with two issuers and two investors. In reality investors exhibited flight to quality by purchasing U.S. Treasury bonds in this period. This is somewhat ironic as the sub-prime shock is originated in the U.S.

Our model extends the framework of Fernando (2003) to two risky assets with returns that may be correlated.[86] Consider an exchange economy with a group of *M* risk-averse investors. There are three dates, t = 0, 1, and 2. At time $t = 0$ each investor is endowed with one unit of each asset: two risky bonds with superscripts *A* and *B* and one riskless asset. At time $t = 1$, trading happens. At time $t = 2$, both risky bonds mature and pay a random quantity of the numeraire riskless asset, $E(\tilde{v}^A)$ and $E(\tilde{v}^B) > 1$. These bonds' expected returns are common knowledge (i.e., there is no asymmetric information) and are normally distributed with means, $\bar{v}^A$ and $\bar{v}^B$, variances, $\sigma_v^{2,A}$ and $\sigma_v^{2,B}$, and correlation, $\rho_v^{A,B}$. The risk-free rate is assumed to be zero. Investors maximize a negative exponential utility function of their terminal wealth at time $t = 2$, $u(w_2) = -\exp(-aw_2)$, where $a > 0$ is the coefficient of absolute risk aversion.

All investors are identical except that they experience heterogeneous liquidity shocks. The idea is that investors with lower exposure to liquidity shocks will provide liquidity to those with higher exposure via trading , therefore, enjoy a higher risk-adjusted return. In our setting, the liquidity shock faced by an investor i, $\tilde{\theta}_i$, is unknown at $t = 0$ and realized at time $t = 1$ with the distribution being known ex ante at time $t = 0$. The liquidity shock can arise due to a broad range of events that affect the investor's valuation of the risky asset without new information about the fundamental value. Following Karpoff (1986), Michaely and Villa (1995), Michaely, Vila and Wang (1996), and Fernando (2003), the shock is assumed to be additive to investor *i*'s valuation of

[86] Fernando (2003)'s model focuses on liquidity transmission across investors, but ours emphasizes on how liquidity transmits across securities.

payoff $\tilde{v}$ on the risky bond.[87] Therefore, the shock changes each investor's valuation of the asset without affecting the asset's fundamental return.

The liquidity shock can be decomposed into two random additive components, one being systematic and the other being idiosyncratic. The systematic shock is defined as a shock that hits all investors equally, whereas the residual shock after removing the systematic shock is denoted as the idiosyncratic shock. Then the shocks to bonds *A* and *B* as seen by investor *i* can be written as

$$\begin{aligned} \tilde{\theta}_i^A &= \tilde{\delta} + \tilde{\varepsilon}_i^A, \\ \tilde{\theta}_i^B &= \tilde{\delta} + \tilde{\varepsilon}_i^B, \end{aligned} \tag{4.1}$$

where $\tilde{\delta}$ is the systematic component (which is perfectly correlated across all bonds and investors, so bears no subscript *i* and no superscript *A* or *B*), and $\tilde{\varepsilon}_i^A$ and $\tilde{\varepsilon}_i^B$ are the idiosyncratic liquidity shocks to bonds *A* and *B* faced by investor *i*. All $\tilde{\delta}$, $\tilde{\varepsilon}_i^A$ and $\tilde{\varepsilon}_i^B$ are assumed to be *i.i.d.* and normally distributed with common means of zero, but different variances of $\sigma_\delta^2, \sigma_\varepsilon^{2,A}$ and $\sigma_\varepsilon^{2,B}$ respectively. These shocks affect investors' valuation of the two risky assets and induce trading to rebalance their portfolios as soon as a shock is realized at time t = 1.

---

[87] In general, liquidity shocks can be a result of changes in preferences (or uncertainty about preference) and changes in endowments. For a tractability reason, we restrict the definition of liquidity shocks in this paper to any changes in investors' valuation that does not have any impact on the asset's fundamentals.

Trading occurs in a simple batch market with all trades clearing at a single price at time t = 1. For simplicity, we assume there are no transaction costs in trading.[88] Investor i rebalances her portfolio in order to maximize the following utility function:

$$\begin{aligned}
&\max E[u(w_{2,i})],\ i \in \mathrm{M}, \\
&w_{2,i} = w_{1,i} + x_{1,i}^{A}(\tilde{v}^{A} + \tilde{\theta}_{i}^{A} - \tilde{p}_{1}^{A}) + x_{1,i}^{B}(\tilde{v}^{B} + \tilde{\theta}_{i}^{B} - \tilde{p}_{1}^{B}), \\
&w_{1,i} = w_{0,i} + (\tilde{p}_{1}^{A} - \tilde{p}_{0}^{A}) + (\tilde{p}_{1}^{B} - \tilde{p}_{0}^{B}),
\end{aligned} \tag{4.2}$$

where $w_{t,i}$ is the wealth of investor i at the end of time t, $x_{1,i}^{A}$ and $x_{1,i}^{B}$ is the amount of bonds A and B held by investor i at the end of time t = 1, $\tilde{p}_t$ is the bond price at time t. Other variables were already mentioned before.

4.3.2 Equilibrium prices and optimal holdings

We can solve for prices of the two bonds (p_t^A and p_t^B) and holdings by investor i ($x_{i,t}^{A}$ and $x_{i,t}^{B}$) at times t = 0 and 1 using a recursive method. At time t = 1 the clearing prices and equilibrium holdings of bonds A and B by investor i, p_1 and $x_{1,i}$, are given by[89]

$$\begin{aligned}
&p_1^A = \overline{v}^{A} + \hat{\delta} + \hat{\varepsilon}_M^A - a(\sigma_v^{2,A} + \rho_v^{A,B}\sigma_v^A\sigma_v^B), \\
&p_1^B = \overline{v}^{B} + \hat{\delta} + \hat{\varepsilon}_M^B - a(\sigma_v^{2,B} + \rho_v^{A,B}\sigma_v^A\sigma_v^B), \\
&x_{1,i}^{A} = \frac{(\hat{\varepsilon}_i^A - \hat{\varepsilon}_M^A) + \left\{(\hat{\varepsilon}_M^B - \hat{\varepsilon}_i^B)\rho_v^{A,B}\dfrac{\sigma_v^A}{\sigma_v^B}\right\} + a\sigma_v^{2,A}(1-\rho_v^{2,A,B})}{a\sigma_v^{2,A}(1-\rho_v^{2,A,B})}, \\
&x_{1,i}^{B} = \frac{(\hat{\varepsilon}_i^B - \hat{\varepsilon}_M^B) + \left\{(\hat{\varepsilon}_M^A - \hat{\varepsilon}_i^A)\rho_v^{A,B}\dfrac{\sigma_v^B}{\sigma_v^A}\right\} + a\sigma_v^{2,B}(1-\rho_v^{2,A,B})}{a\sigma_v^{2,B}(1-\rho_v^{2,A,B})},
\end{aligned} \tag{4.3}$$

[88] The main results are not changed and the testing applications are still the same even if we introduce transaction costs.

[89] See Appendix 4A for a proof of this section.

where $\hat{\delta}$ and $\hat{\varepsilon}_i$ denote the realizations of $\tilde{\delta}$ and $\tilde{\varepsilon}_i$. $\hat{\varepsilon}_M^{A,B} = \sum_{i=1}^{M} \hat{\varepsilon}_i^{A,B} \Big/ M$ are the market-average realization of idiosyncratic liquidity shocks with respect to bonds *A* or *B* across the investor base *M*.

When the number of investors approaches infinity ($M \to \infty$), the bond price at time $t = 1$ reflects the expected bond return, $\bar{v}$, the realized systematic (undiversified) component, $\hat{\delta}$, the coefficient of absolute risk aversion, *a*, the return volatility, σ^2_V, and the return correlation, $\rho_V^{A,B}$. In this case $\hat{\varepsilon}_M^A$ and $\hat{\varepsilon}_M^B \to 0$ and the realized idiosyncratic shock is not priced. Intuitively, only common risk, $\hat{\delta}$, which cannot be diversified away by trading, is important when the investor base is large enough. Hence, only that is priced. The stronger the positive correlation in returns, the lower is the price of both bonds since the investor is more unable to diversify. Trading is a result of the risk-sharing of heterogeneous investors, who have different exposures to realizations of idiosyncratic shocks at time $t = 1$. The valuation of bonds by investors will differ from market prices due to investors' heterogeneous exposures to the shocks. Investors, who experience a positive (relatively to the market) shock, will value a security more than those, who are hit by a negative one. Therefore, the shifting of a liquidity shock via trading is beneficial to both agents. Low (high) exposure investors receive a higher (lower) risk-adjusted return. This difference in trading demand as a result of a different exposure to shocks is only transmitted from one asset to another if the two assets' returns are correlated.

At time t = 0, the equilibrium prices are given by[90]

$$
\begin{aligned}
p_0^A &= \bar{v}^A - a(\sigma_v^{2,A} + \rho_v^{A,B}\sigma_v^A\sigma_v^B + \sigma_\delta^2 + \frac{\sigma_\varepsilon^{2,A}}{M}),\\
p_0^B &= \bar{v}^B - a(\sigma_v^{2,B} + \rho_v^{A,B}\sigma_v^A\sigma_v^B + \sigma_\delta^2 + \frac{\sigma_\varepsilon^{2,B}}{M}).
\end{aligned}
\tag{4.4}
$$

Similarly, the price at time t = 0 incorporates the liquidity discount ($a(\sigma_\delta^2 + \frac{\sigma_\varepsilon^{2,A}}{M})$), reflecting the possible liquidity shocks in the future at time t = 1. Again, as $M \to \infty$, only systematic liquidity risk is relevant in determining prices.

4.3.3 Trading volume and volatility

The quantity traded by investor i in bonds A and B at time t = 1 is given by

$$
\begin{aligned}
\Delta x_{1,i}^A &= \frac{(\hat{\varepsilon}_i^A - \hat{\varepsilon}_M^A) + (\hat{\varepsilon}_M^B - \hat{\varepsilon}_i^B)\rho_v^{A,B}\dfrac{\sigma_v^A}{\sigma_v^B}}{a\sigma_v^{2,A}(1-\rho_v^{2,A,B})},\\
\Delta x_{1,i}^B &= \frac{(\hat{\varepsilon}_i^B - \hat{\varepsilon}_M^B) + (\hat{\varepsilon}_M^A - \hat{\varepsilon}_i^A)\rho_v^{A,B}\dfrac{\sigma_v^B}{\sigma_v^A}}{a\sigma_v^{2,B}(1-\rho_v^{2,A,B})},
\end{aligned}
\tag{4.5}
$$

where $\Delta x_{1,i} = x_{1,i} - 1$. From Equation (4.5), the trading volume of bond A depends on realizations of (i) bond A's own idiosyncratic shock and (ii) the idiosyncratic shock of bond B given that A and B returns are correlated. If we have a trading cost when investors rebalance their portfolios at time t = 1, everything is still the same except that

[90] Even though trading is allowed at time t = 0. The optimum holdings of bonds are still the same as investors' initial endowment (See Appendix A). Therefore no trading occurs at time t = 0.

bond *A*'s transaction cost affects trading volume of both bonds *A* and *B*.[91] Note that investors trade only if they are different in some way. In our model, trading occurs only if liquidity shocks have different impacts across investors via the idiosyncratic liquidity shock.[92] Therefore, idiosyncratic shocks that have different effects across securities, but are common across investors do not generate investors' trading. However, assets' prices will be adjusted accordingly.

The expectation at time t = 0 of trading volume for each investor at time t = 1 is given by

$$
\begin{aligned}
E_{t=0}\left(|\,\Delta x_{1,i}^{A}\,|\right) &= \frac{1}{a\sigma_{v}^{2,A}(1-\rho_{v}^{2,A,B})}\cdot\sqrt{\frac{2}{\pi}\left[\frac{\sigma_{\varepsilon}^{2,A}(M-1)}{M}+\frac{\sigma_{\varepsilon}^{2,B}(M-1)}{M}\left(\rho_{v}^{2,A,B}\frac{\sigma_{v}^{2,A}}{\sigma_{v}^{2,B}}\right)\right]},\\
E_{t=0}\left(|\,\Delta x_{1,i}^{B}\,|\right) &= \frac{1}{a\sigma_{v}^{2,B}(1-\rho_{v}^{2,A,B})}\cdot\sqrt{\frac{2}{\pi}\left[\frac{\sigma_{\varepsilon}^{2,B}(M-1)}{M}+\frac{\sigma_{\varepsilon}^{2,A}(M-1)}{M}\left(\rho_{v}^{2,A,B}\frac{\sigma_{v}^{2,B}}{\sigma_{v}^{2,A}}\right)\right]}.
\end{aligned}
\tag{4.6}
$$

As can be seen from Equation (4.6), the expected trading volume of bond *A* increases with 1) the idiosyncratic liquidity risk of bond *A*, $\sigma_{\varepsilon}^{2,A}$, and 2) the idiosyncratic liquidity risk of bond *B*, $\sigma_{\varepsilon}^{2,B}$, given that bond *A* and *B* returns are correlated, i.e., $\rho_{v}^{A,B} \neq 0$.

---

[91] If the transaction cost is a function of $c\cdot\Delta x^2_1$, where c is per unit transaction cost and we assume that $c^A \geq 0$ and $c^B = 0$ (i.e., there is no transaction cost in trading bond *B*), the trading volume of bonds *A* and *B* by investor i at time t = 1 is given by

$$
\Delta x_{1,i}^{A} = \frac{(\hat{\varepsilon}_{i}^{A}-\hat{\varepsilon}_{M}^{A})+(\hat{\varepsilon}_{M}^{B}-\hat{\varepsilon}_{i}^{B})\rho_{v}^{A,B}\dfrac{\sigma_{v}^{A}}{\sigma_{v}^{B}}}{\left[a\sigma_{v}^{2,A}(1-\rho_{v}^{2,A,B})+2c^{A}\right]},
$$

$$
\Delta x_{1,i}^{B} = \frac{\left\{(\hat{\varepsilon}_{i}^{B}-\hat{\varepsilon}_{M}^{B})(\dfrac{2c^{A}}{a\sigma_{v}^{2,A}}+1)\right\}+(\hat{\varepsilon}_{M}^{A}-\hat{\varepsilon}_{i}^{A})\rho_{v}^{A,B}\dfrac{\sigma_{v}^{B}}{\sigma_{v}^{A}}}{\left[a\sigma_{v}^{2,B}(1-\rho_{v}^{2,A,B})+2c^{A}\dfrac{\sigma_{v}^{2,B}}{\sigma_{v}^{2,A}}\right]}.
$$

[92] As an example, the across-investor idiosyncratic liquidity shocks affect individual agent's asset valuation differently because of different tax treatment of dividends (or bond coupons) and capital gains for each investor. See Michaely and Vila (1995) for more detail.

The price volatility at time t = 1 can be directly derived from Equation (4.3) as follows:

$$\sigma_{p_1}^{2,A} = \sigma_\delta^2 + \frac{\sigma_\varepsilon^{2,A}}{M},$$
$$\sigma_{p_1}^{2,B} = \sigma_\delta^2 + \frac{\sigma_\varepsilon^{2,B}}{M}. \tag{4.7}$$

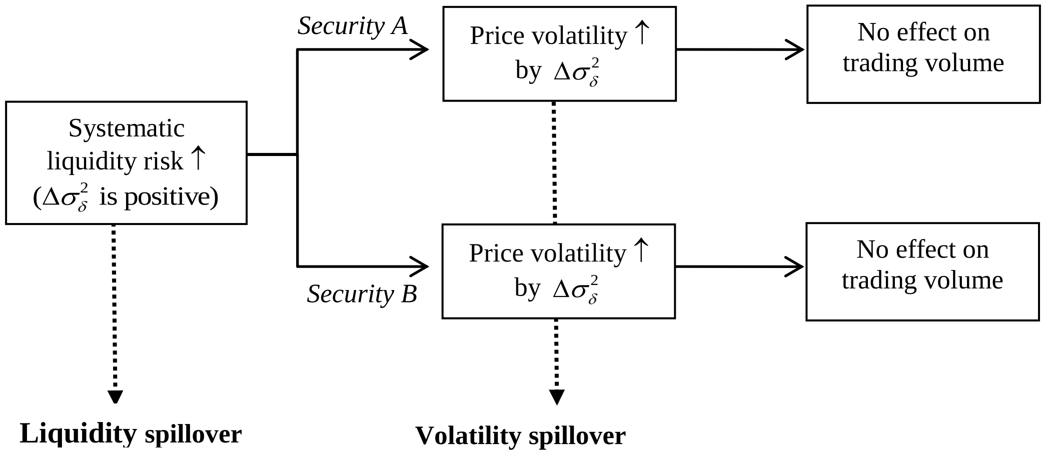
The price volatility is a result of both systematic and idiosyncratic liquidity shocks, but the importance of idiosyncratic shocks diminishes once the market has a large number of investors. As in the no-trade equilibrium of Milgrom and Stokey (1982), the systematic liquidity shock exacerbates price volatility because the price will adjust to reflect the shock, but investors are unable to mutualize their liquidity shocks by trading at time t = 1. Therefore the secondary market collapses. Fleming and Remolona (1999) also show empirically that price responses to public information do not require trading.

4.3.4 Model implications: liquidity spillovers

Our model implies that systematic and idiosyncratic liquidity shocks deliver different results in terms of return and volatility commonalities.

By definition, a systematic shock is perfectly correlated across assets, so that commonality of this liquidity shock arises by default. As a result, we should observe that commonality in liquidity coincides with that in volatility, but not necessarily with that in returns (unless investors do not have the same exposures to systematic liquidity risk). Figure 4-1 summarizes the mechanism by which volatility spills over if there is systematic liquidity risk. For example, a market-wide crisis, such as the U.S. subprime crisis of 2007, simultaneously increases the volatility of all emerging-market bonds even though their fundamentals are not closely related.

Figure 4-1: Systematic liquidity shock and co-movement in liquidity and volatility



By contrast, if we experience an idiosyncratic shock across investors (for example, an illiquidity shock in bond *A*, which hits investor *i*, but not investor *j*), there will be no subsequent effect on prices of bonds *A* and *B* and commonality in volatility will not be observed. However, there will be a liquidity spillover upon the arrival of the idiosyncratic liquidity shock due to concentration of trading volume in bond *B*, given that returns on *A* and *B* are correlated or it is difficult to trade bond *A* due to a friction in the market.[93] Figure 4-2 summarizes this mechanism. The higher is the correlation in returns, the greater is the trading concentration and, hence, the larger is the liquidity spillover. For instance, an idiosyncratic liquidity shock specific to one nation, such as the Greek crisis of 2010, induces the trading of Greek bonds as well as that of substitute bonds issued by other countries (as in our stylized example, Portugal). In our model, idiosyncratic liquidity spillovers are caused by trading among substitute bonds, whose prior returns are correlated with Greek bonds.

[93] In this model, what transmits across assets is the trading volume and it is, however, unclear which aspect of liquidity is transferred following transition of trading volume.

Figure 4-2: Idiosyncratic liquidity shock and co-movement in liquidity and return

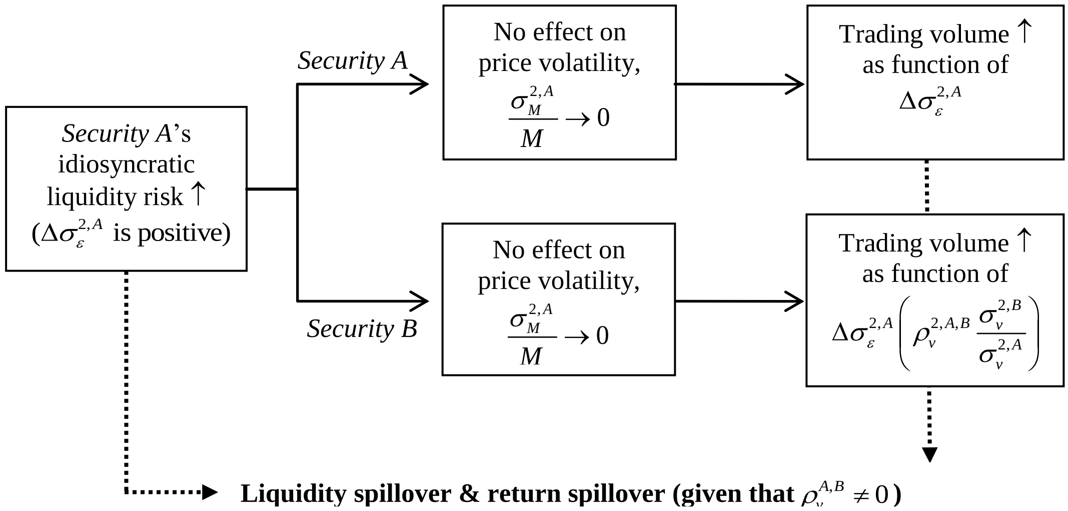
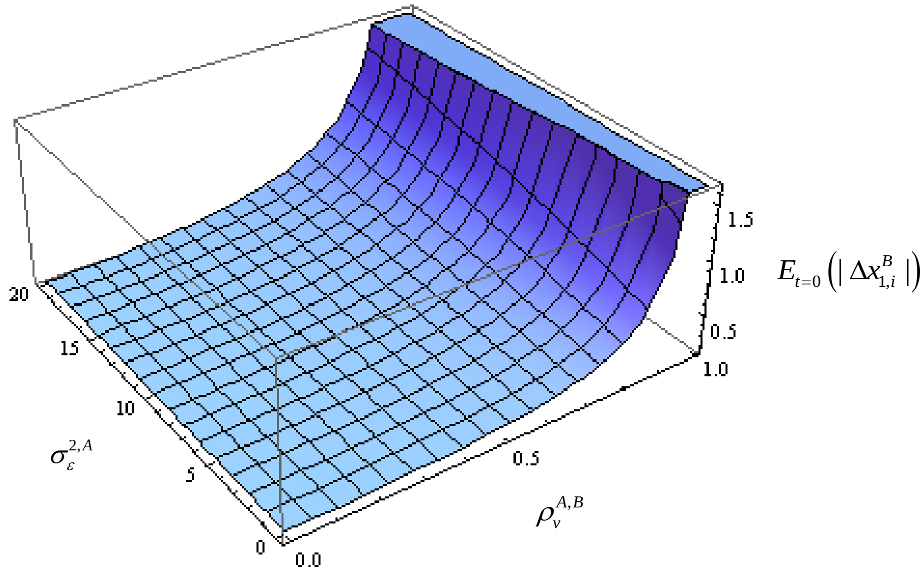


Figure 4-3 plots the expected trading volume of bond *B* at time $t = 0$ of investor *i*, $E_{t=0}\left(|\Delta x_{1,i}^{B}|\right)$, as computed in Equation (4.6) against the idiosyncratic liquidity risk of bond *A*, $\sigma_{\varepsilon}^{2,A}$, and the return correlation of bonds *A* and *B*, $\rho_v^{A,B}$. The expected trading volume of bond *B* monotonically increases with the idiosyncratic risk of bond *A*. The return correlation of bonds *A* and *B* is the key determinant of trading volume because it allows investors to offset the illiquidity shock in one security by trading in another. This view is also supported by Caballe and Krishman (1994) and Huberman and Halka (2001). The former argues that whether or not liquidity shocks in the market are correlated, a spillover in volume occurs only when fundamentals are correlated. The latter provides empirical evidence that the availability of a substitute asset causes a liquidity spillover, which leads to commonality of liquidity.

Figure 4-3: Return correlation, idiosyncratic liquidity risk of bond *A* and expected trading volume spilled over to bond *B*

This figures plots the expected trading volume of bond *B* at time t = 0 of investor i, $E_{t=0}\left(|\Delta x_{1,i}^{B}|\right)$ as computed in Equation (4.6) against the idiosyncratic liquidity risk of bond *A*, $\sigma_{\varepsilon}^{2,A}$, and the return correlation of bonds *A* and *B*, $\rho_{v}^{A,B}$. Other parameters in Equation (4.6) are set as follows: a = 3, $\sigma_{\varepsilon}^{2,B}$ = 5%, $\sigma_{v}^{2,A}$ = 5% and $\sigma_{v}^{2,B}$ = 5%.



In summary, our model predicts that commonality in liquidity should coincide with that in volatility if the liquidity shocks are caused by a systematic factor. On the contrary, spillovers in liquidity caused by an idiosyncratic shock should be associated with spillovers in returns. Before turning to empirical tests of the model, the next section describes the data used and their key features.

4.4 Data and Summary Statistics

The data are obtained from J.P. Morgan. Our main test assets are bonds in the Emerging Market Bond Index (EMBI).[94] The EMBI bonds are 1) denominated in U.S. dollar with outstanding face-value of 500 million U.S. dollar or more, 2) issued by sovereign or quasi-sovereign entities of eligible emerging countries, 3) at least 2.5 years away from maturity at the inclusion (a bond is removed from the EMBI when its maturity is less than 12 months), 4) accessible to international investors, 5) issued with legal jurisdiction that is domestic to a G7 country and 6) able to settle internationally. Since all bonds are issued in U.S. dollar, we do not have to be concerned with currency movements. The following 35 countries in three regions, Asia, Europe and Latin America, are included in this study.[95]

Asia	Europe	Latin America
1. China (CN)	1. Bulgaria (BG)	1. Argentina (AR)
2. Indonesia (ID)	2. Serbia (CS)	2. Brazil (BR)
3. Korea (KR)	3. Greece (GR)	3. Belize (BZ)
4. Kazakhstan (KZ)	4. Croatia (HR)	4. Chile (CL)
5. Lebanon (LB)	5. Hungary (HU)	5. Columbia (CO)
6. Sri Lanka (LK)	6. Poland (PL)	6. Dominican (DO)
7. Malaysia (MY)	7. Russia (RU)	7. Ecuador (EC)
8. Philippines (PH)	8. Turkey (TR)	8. Jamaica (JM)
9. Pakistan (PK)	9. Ukraine (UA)	9. Mexico (MX)
10. Thailand (TH)		10. Panama (PA)
11. Vietnam (VN)		11. Peru (PE)
		12. El Salvador (SV)
		13. Trinidad Tobago (TT)
		14. Uruguay (UY)
		15. Venezuela (VE)

[94] EMBI is arguably the most comprehensive U.S. dollar emerging market debt benchmark. It includes Brady bonds, Eurobonds and traded loans issued by sovereign and quasi-sovereign entities.

[95] In fact, EMBI also includes the countries from Africa. However, their market share is very small (less than 3% of the total EMBI market capitalization). For the sake of parsimony, we therefore exclude them from our regression analyses. We will, however, provide their simple statistics for cross-region comparisons.

The sample period runs from 31 December 1993 to 15 February 2010.[96] The data (on bid and ask prices, bond returns, and market capitalizations) are collected on a daily basis. In our main specification, we group the bonds into their countries and regions of issuance. The market value of EMBI is 342 billion U.S. dollar at the end of 2009 with 215 bond issues. Latin American countries have the largest proportion (46%) of the total market capitalization. European and Asian countries account for 28% and 24% respectively. The majority of the bonds (55%) are of investment grade. More than 90% are above BB. The average maturity is 11.98 years. Figure 4-4 shows the composition of the EMBI market capitalization by region, credit rating, and maturity.

4.4.1 Bond returns and volatility

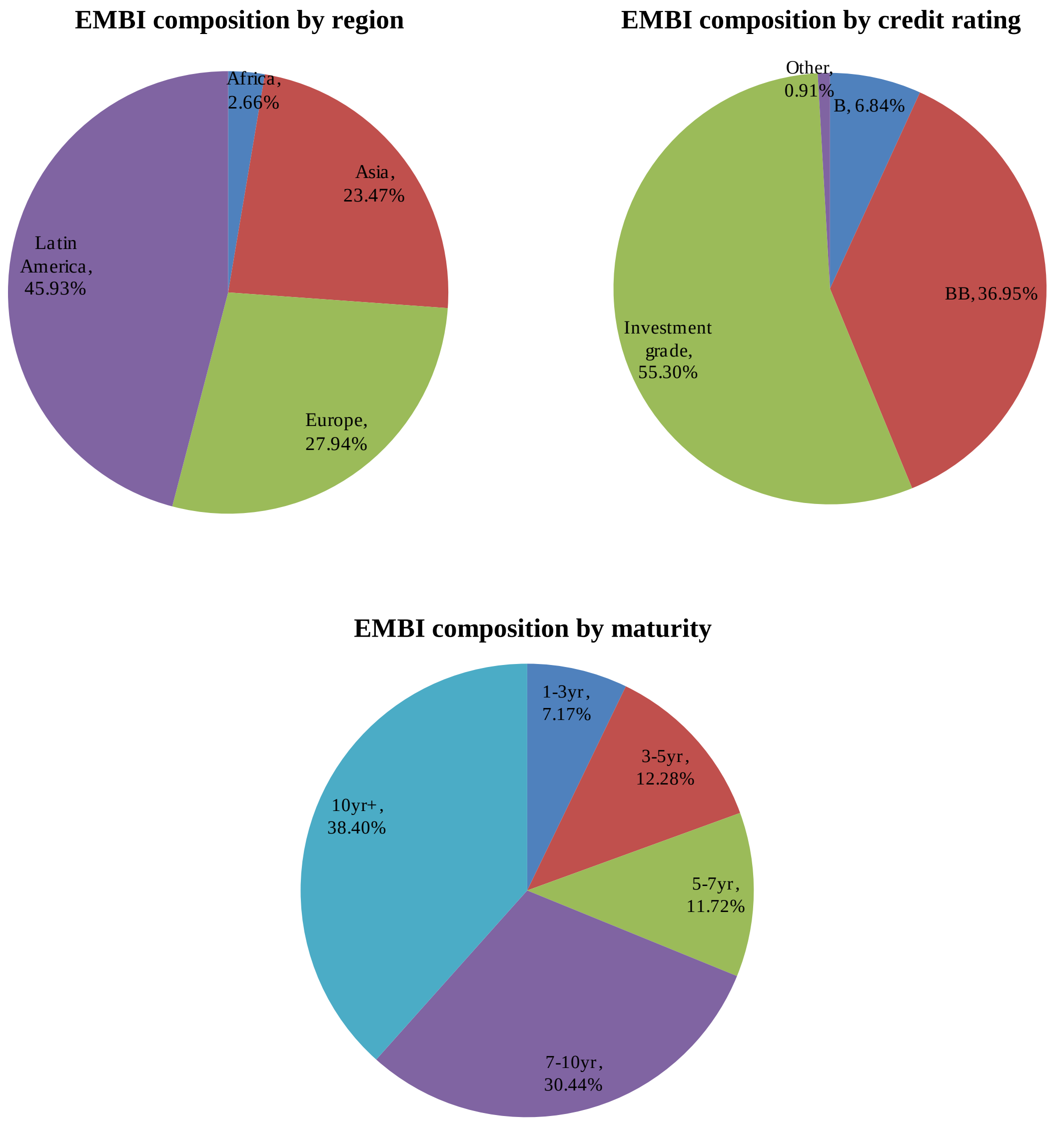
The daily total return for a bond between period $t-1$ and t is calculated as

$$R_t^j = \left(\frac{P_t^j + AI_t^j + Coupon_t^j}{P_{t-1}^j + AI_{t-1}^j} \right) - 1, \tag{4.8}$$

where R^j_t is total return of bond j at month t incorporating principal and interest, P^j_t is closing clean price for the bond j at month t, AI^j_t is accrued interest, which is the coupon payment scaled by the ratio of days since the last payment date to the days between last payment and next payment and $Coupon^j_t$ is the coupon payment, if any, of bond j at month t. We calculate the bond portfolios' returns using market value weighting to ensure the portfolio investability.

[96] This is when the data on EMBI were first available.

Figure 4-4: EMBI composition by region, credit rating and maturity at the end of 2009



From bond return series, we compute a bond's daily volatility using an exponentially-weighted moving average (EWMA) method, where the higher weight is given to the more recent observations:

$$VOL^{j} = \sqrt{(1-\lambda)\sum_{t=1}^{T}\lambda^{t-1}(R_t^{j} - \bar{R}^{j})^2}, \tag{4.9}$$

where the smoothing or decay parameter, λ, is set to be 0.94 with a rolling window of 75 days.

4.4.2 Illiquidity measures

With the EMBI data set, we can construct the illiquidity measure for each bond in each country by its quoted bid/ask spread.[97] At each day t during the study period, the quoted bid/ask spread, C^j_t, is collected for each individual bond j, where C^j_t is the ratio of the quoted bid/ask spread to the bid/ask midpoint:

$$C_t^j = \frac{Ask_t^j - Bid_t^j}{Mid_t^j}, \tag{4.10}$$

where $Mid_t^j = (Ask_t^j + Bid_t^j)/2$, Ask_t^j and Bid_t^j are mid, ask and bid quoted prices of bond j at day t. Similarly, we use market-weighted to calculate the illiquidity at the portfolio level.

Table 4-1 provides summary statistics of the return, volatility, and illiquidity cost as measured by the percentage bid/ask spread for all bonds in the EMBI and for regional portfolios. The market-wide bid/ask spread and volatility are high during periods of liquidity crises in emerging countries such as the Mexican Peso devaluation (December 1994), the Asian crisis (mid 1997), the Russian Ruble devaluation (August 1998), the LTCM crisis (September 1998), the Brazilian Real devaluation (January 1999), the Turkish Lira devaluation (March 2001), Argentina's debt moratorium (December 2001), and the U.S. subprime crisis (2008-2009). However, there is no clear pattern for return series across regions.

[97] For international bond markets, the trading volume data are usually unavailable. Hence, we cannot compute the volume-based measure of illiquidity such as trading volume, turnover ratio, Amihud's (2002) measure of illiquidity (ILLIQ) and Checko (2006)'s latent liquidity measure. However, many studies, for example, D'Souza, Gaa and Young (2003) and Fleming (2003) find that the bid/ask spread is one of the most suitable liquidity measures as it is highly correlated with other measures.

Table 4-1: Summary statistics of the return, volatility and illiquidity measures at the portfolio level

This table provides the year-by-year summary statistics on all U.S. dollar sovereign bonds in the EMBI. The daily sample runs from January 1994 to December 2009. The means of daily bid/ask spreads, returns and volatility are reported. The number in the parentheses is standard deviation. The market weighting method is employed. Bonds are sorted into the region of issuance, which is Africa, Asia, Europe and Latin America.

All issues	1994–95	1996–97	1998–99	2000–01	2002–03	2004–05	2006–07	2008–09	1994–2009
Bid/ask spread	0.75	0.41	0.98	0.79	0.79	0.62	0.50	1.12	0.75
	(0.25)	*(0.19)*	*(0.47)*	*(0.15)*	*(0.12)*	*(0.10)*	*(0.07)*	*(0.60)*	*(0.40)*
Return	0.02	0.07	0.02	0.03	0.07	0.04	0.03	0.02	0.04
	(1.27)	*(0.75)*	*(1.11)*	*(0.63)*	*(0.47)*	*(0.39)*	*(0.24)*	*(0.65)*	*(0.78)*
Volatility	1.61	0.97	1.41	0.91	0.68	0.57	0.35	0.72	0.89
	(0.91)	*(0.59)*	*(1.00)*	*(0.32)*	*(0.29)*	*(0.20)*	*(0.12)*	*(0.67)*	*(0.80)*
Bid/ask spread (by region)									
Africa	1.69	0.86	2.49	2.53	1.93	1.29	0.94	1.87	1.70
	(0.78)	*(0.50)*	*(1.38)*	*(0.49)*	*(0.43)*	*(0.25)*	*(0.17)*	*(1.30)*	*(1.05)*
Asia	0.88	0.55	1.36	0.57	0.44	0.53	0.45	1.35	0.77
	(0.35)	*(0.33)*	*(0.62)*	*(0.09)*	*(0.05)*	*(0.09)*	*(0.09)*	*(1.01)*	*(0.66)*
Europe	0.66	0.40	1.52	0.82	0.50	0.48	0.39	1.27	0.77
	(0.33)	*(0.22)*	*(0.82)*	*(0.17)*	*(0.11)*	*(0.09)*	*(0.07)*	*(0.91)*	*(0.65)*
Latin America	0.71	0.37	0.74	0.71	0.88	0.62	0.50	0.87	0.68
	(0.25)	*(0.17)*	*(0.37)*	*(0.20)*	*(0.18)*	*(0.11)*	*(0.07)*	*(0.26)*	*(0.29)*
Return (by region)									
Africa	0.04	0.09	0.04	0.06	0.07	0.03	0.03	0.02	0.05
	(1.46)	*(0.78)*	*(1.15)*	*(0.69)*	*(0.42)*	*(0.22)*	*(0.14)*	*(0.45)*	*(0.80)*
Asia	0.02	0.01	0.05	0.04	0.04	0.03	0.03	0.03	0.04
	(0.57)	*(0.32)*	*(0.52)*	*(0.24)*	*(0.29)*	*(0.28)*	*(0.20)*	*(0.77)*	*(0.47)*
Europe	0.03	0.11	-0.05	0.12	0.09	0.04	0.03	0.02	0.05
	(1.72)	*(1.08)*	*(1.69)*	*(0.80)*	*(0.48)*	*(0.42)*	*(0.21)*	*(0.80)*	*(1.06)*
Latin America	0.02	0.08	0.03	0.00	0.07	0.04	0.04	0.01	0.04
	(1.36)	*(0.80)*	*(1.27)*	*(0.79)*	*(0.69)*	*(0.48)*	*(0.31)*	*(0.72)*	*(0.89)*
Volatility (by region)									
Africa	2.03	1.08	1.44	0.99	0.60	0.32	0.21	0.54	0.87
	(0.88)	*(0.46)*	*(0.99)*	*(0.41)*	*(0.27)*	*(0.13)*	*(0.05)*	*(0.45)*	*(0.82)*
Asia	0.63	0.42	0.70	0.36	0.44	0.43	0.30	0.81	0.51
	(0.32)	*(0.19)*	*(0.43)*	*(0.10)*	*(0.12)*	*(0.11)*	*(0.09)*	*(0.82)*	*(0.48)*
Europe	2.16	1.36	2.31	1.22	0.70	0.61	0.31	0.86	1.16
	(1.04)	*(0.84)*	*(1.26)*	*(0.31)*	*(0.28)*	*(0.23)*	*(0.10)*	*(0.86)*	*(1.08)*
Latin America	1.76	1.05	1.56	1.12	0.98	0.70	0.45	0.85	1.04
	(0.97)	*(0.63)*	*(1.18)*	*(0.45)*	*(0.43)*	*(0.24)*	*(0.18)*	*(0.66)*	*(0.88)*

4.4.3 Innovations in illiquidity, returns and volatility

As the illiquidity cost measured by bid/ask spread in Section 4.4.2 is highly persistent and we are interested in the transmission of liquidity shocks, we need to calculate liquidity shocks, which satisfy the stationarity condition in a time-series analysis. For example, the bid/ask spread for the market-wide portfolio has a high daily autocorrelation of 0.96.[98] We compute the innovations in illiquidity (termed "liquidity shock" for the rest of the paper), returns and volatility using autoregressive processes with four lags, AR(4).[99] The remaining autocorrelations of these innovations are very low, for example, they are respectively 0.010, 0.000, −0.002 for innovations in liquidity, return, and volatility for the market-wide portfolio. Figure 4-5 shows the time series of the market-wide (EMBI) illiquidity cost, measured by percentage quoted bid/ask spread, and innovations in that series based on the AR(4) process. Both series are very volatile during global liquidity crises as mentioned earlier.

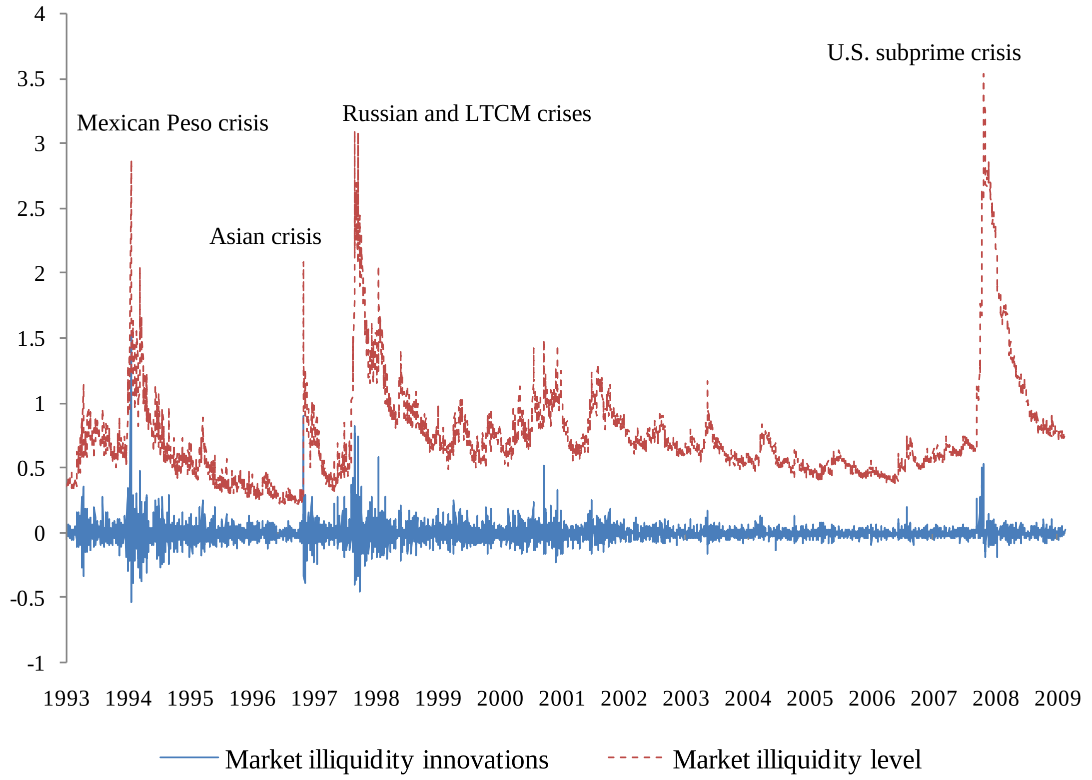
For an initial demonstration that there exist commonalities in liquidity, returns and volatility, Figure 4-6 plots the average-across-region 100-day rolling window correlations of innovations in liquidity, returns and volatility for each region (Africa, Asia, Europe and Latin America) with those of each other region. Not only do these average correlations seem to move together closely, but they are also time-varying with abrupt changes during 1994−1995 (Mexican Peso crisis), 1997−1998 (Asian and LTCM crisis), and 2008−2009 (U.S. subprime crisis).

[98] Autocorrelation of market-wide return and volatility series are 0.17 and 0.98 respectively.

[99] Admittedly, choice of the number of lags for an AR process is arbitrary. The more lags in AR do not show much further improvement both in terms of an R^2 and a degree of autocorrelation.

Figure 4-5: Time-series of daily market-wide illiquidity cost (bid/ask spread) and its innovations

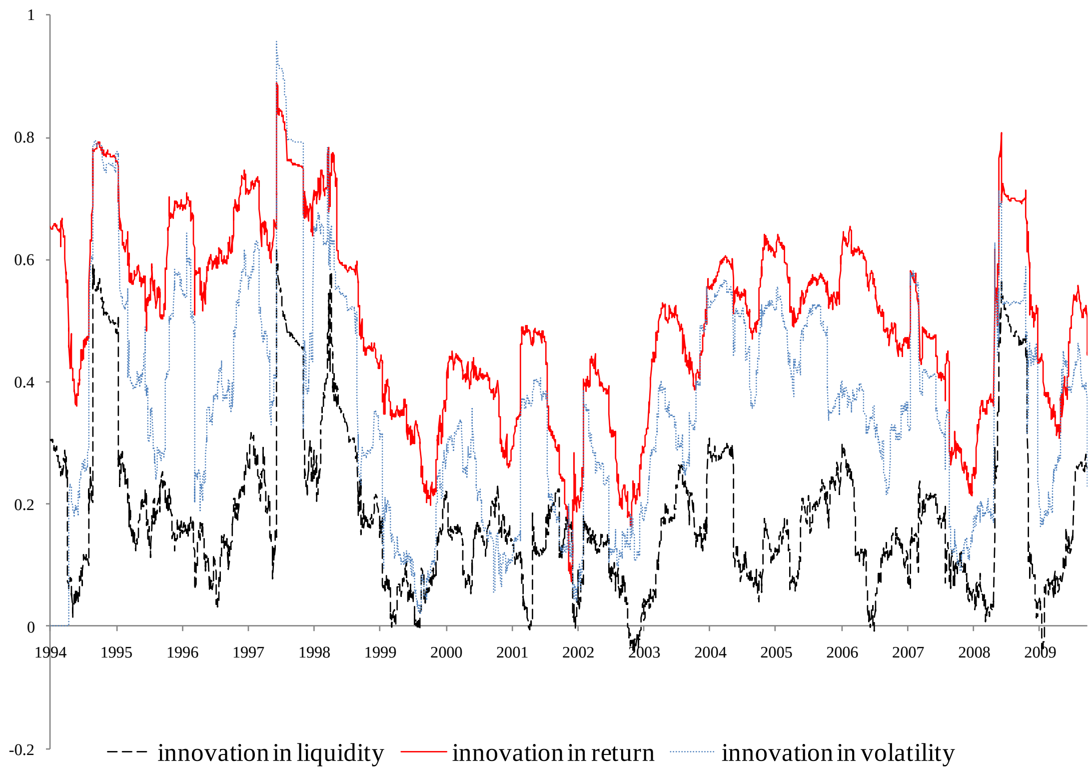
This figure depicts time series of illiquidity cost and its innovation for the global or market-wide portfolio. The illiquidity cost is the percentage quoted bid/ask spread as computed by (quoted ask price$_t$ – quoted bid price$_t$)/ mid price$_t$. The innovation is computed using an AR(4) specification. The market portfolio is formed using the value weighting method.



The next two sections present the empirical analyses. Section 4.5 employs a vector autoregression (VAR) model to identify the patterns of liquidity, return and volatility transmissions. Section 4.6 estimates commonality measures for liquidity, returns and volatility. These results are then used in a further regression to investigate whether return or volatility commonality is more associated with the liquidity commonality in both cross-section (across countries) and times-series (across regions).

Figure 4-6: Time-series of correlations in liquidity, return and volatility across regions

This figure plots the average-across-region correlations of innovation variables in one region (Africa, Asia, Europe and Latin American) and those of other regions (the aggregate market). Interested variables are innovation in illiquidity cost (percentage bid/ask spread), returns and volatility. The innovation is calculated using the autoregressive process with four lags. Time-series correlations for each region are computed using 100-day rolling windows.



4.5 Spillovers in Liquidity, Returns and Volatility: Empirical Tests and Results

From the model in Section 4.3, it is not difficult to visualize liquidity transmission in the case of two assets with different illiquidity costs. Once a group of investors is hit by an idiosyncratic liquidity shock in one asset, given that two assets are substitutes, there will be more demand by investors for trading in both securities in order to minimize the adverse impact of this shock on their terminal wealth. Particularly if securities have transaction cost, investors have to sell liquid securities before they sell illiquid securities to minimize the trading cost. This generates lead and lag patterns from more liquid to less liquid securities. The higher the degree of substitution, the stronger are liquidity spillovers among securities. This view can be called the "Idiosyncratic Liquidity Hypothesis (ILH)".

If the market experiences a systematic shock, we should observe instantaneous movement of liquidity and volatility in both assets, provided that information is effectively processed by market participants. However, if we assume as in Watanabe (2008) that some securities provide stronger information than other securities, investors will update information obtained by observing past signals from the more information-rich securities. To the extent that signals from liquid securities are more informationally meaningful, i.e., they have a higher quality signal, and even though the shock is common across securities, we should observe the impact of a liquidity shock in more liquid securities before less liquid ones.[100] Regardless of the existence of return correlation, this produces liquidity and volatility spillovers among securities with a time lag. We call this the "Systematic Liquidity Hypothesis (SLH)".

[100] One of the reasons of more meaningful signals from liquid securities is that investors are more active in monitoring higher trading-volume and more liquid securities.

We develop a set of testing hypotheses as follows:

4.5.1 Liquidity lead/lag hypothesis

First of all, as an initial and necessary step, we test whether changes in liquidity spill over from one market to another. Note that at this stage we do not consider whether shocks are idiosyncratic or systematic. We test for spillovers by employing the following vector autoregression (VAR) model relating innovations in liquidity to lagged value across regions:

$$\begin{aligned} c_{1,t} &= \alpha_1 + \sum_{t=1}^{J} C_{t-j}\Phi_{1,j}^{C} + \varepsilon_{1,t}, \\ c_{2,t} &= \alpha_2 + \sum_{j=1}^{J} C_{t-j}\Phi_{2,j}^{C} + \varepsilon_{2,t}, \\ c_{3,t} &= \alpha_3 + \sum_{j=1}^{J} C_{t-j}\Phi_{3,j}^{C} + \varepsilon_{3,t}, \end{aligned} \tag{4.11}$$

where

$$\begin{aligned} C_{t-j} &= \begin{bmatrix} c_{1,t-j} & c_{2,t-j} & c_{3,t-j} \end{bmatrix}, \\ \Phi_{k,j}^{C} &= \begin{bmatrix} \phi_{k,j}^{c_1} & \phi_{k,j}^{c_2} & \phi_{k,j}^{c_3} \end{bmatrix}', \end{aligned}$$

where $c_{1,t}$, $c_{2,t}$ and $c_{3,t}$ are the innovations in liquidity (or liquidity shocks as computed in Section 4.4.3) at time t of portfolios of bonds issued by Asia, Euro and Latin America countries, respectively. This grouping (i) enables us to investigate whether there is any transmission of liquidity shock across regions and (ii) is for parsimony of econometric models. Their corresponding capital letter (C_{t-j}) represents row vectors of lag values (lag-j subscripts). Φ is 3x1 (ϕ is a scalar) parameter vectors of coefficients. Scalar α is intercepts. ε_t is error terms. J is the maximum number of lags in the VAR system. We set J equal to four lags for our daily data.[101]

Table 4-2 shows the Equation (4.11) VAR estimation results using the whole sample period. The estimated coefficient of lagged $c_{k,t-j}$ for $c_{i\neq k,t}$ equations are in most cases positive, indicating that there are liquidity spillovers across regions. We observe a significant lead/lag relation in liquidity shocks from the Asian bond portfolio to Europe ($c_{1,t-j} \rightarrow c_{2,t}$) and from Latin America to Asia and Europe ($c_{3,t-j} \rightarrow c_{1,t}$ and $c_{3,t-j} \rightarrow c_{2,t}$), but not the other way around. The spillover effects from Latin America are most powerful in terms of the magnitudes of estimated coefficients and t-statistics. Not surprisingly, the coefficients estimated of lagged $c_{k,t-j}$ for its own $c_{k,t}$ are mostly negative and significant since liquidity shocks (innovations in liquidity) follow a mean-reverting process.[102]

This evidence of liquidity spillovers is consistent with our liquidity lead/lag hypothesis. In addition, the spillover originates from the Latin America sovereign bond market, which is the largest in terms of market capitalization (see Figure 4-4) and has the lowest average bid/ask spread (see Table 4-1) among the three regions.

To ensure that the results are robust over time, we divide the whole sample into four sub-periods, 1994–1997, 1998–2001, 2002–2005 and 2006–2010 (January) and apply the same VAR model as in Equation (4.11). Table 4-3 confirms that there are similar

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[101] We realize that the lead/lag patterns in variables of interest can result from the time-zone difference. Therefore, J needs to be greater than one in order to address this concern. In addition, our observations are based on U.S. working days (i.e., excluding Saturday, Sunday, and U.S. holiday) and therefore the Monday observations incorporate the effects accumulating during the weekend. Information criteria (AIC and SIC) also suggest a lag length up to four.

[102] By contrast, as mentioned before, the liquidity level is persistent.

patterns in liquidity transmission across regions in every sub-period. Liquidity shocks in Latin America's sovereign bonds spill over to emerging Asian and European bond markets. Up to four (daily) lags of the estimated coefficient of lagged $c_{3,t-j}$ for $c_{1,t}$ and lagged $c_{3,t-j}$ for $c_{2,t}$ are significant and positive. Interestingly, during the recent sub-period, 2006–2010 the magnitudes of estimated lagged $c_{k,t-j}$ on $c_{k \neq i,t}$ are larger and remain mostly positive. This suggests that there have been liquidity spillovers all over the world especially during the recent subprime crisis.

Table 4-2: Spillovers in liquidity across regions

This table shows the VAR estimation results on liquidity shocks (interactions). Bonds are sorted into three portfolios based on their region of issuance. Subscript 1 stands for Asia, 2 for Europe and 3 for Latin America. The daily liquidity shocks, c_i, are computed using an AR(4) process of percentage bid/ask spread and they are market-value weighted. α is the intercept. The VAR system of Equation (4.11) is estimated with J = 4 days for a whole sample period, 31 December 1994 to 31 January 2010. The column variables are dependent variables. t-statistics are in the parentheses. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively

	$c_{1,t-1}$		$c_{1,t-2}$		$c_{1,t-3}$		$c_{1,t-4}$	
$c_{1,t}$	-0.026	-(1.555)	-0.008	-(0.467)	0.014	(0.878)	0.038[b]	(2.341)
$c_{2,t}$	0.115[c]	(4.393)	0.174[c]	(6.682)	0.029	(1.104)	0.098[c]	(3.813)
$c_{3,t}$	0.014	(0.942)	0.040[c]	(2.671)	0.000	(0.001)	0.057[c]	(3.872)
	$c_{2,t-1}$		$c_{2,t-2}$		$c_{2,t-3}$		$c_{2,t-4}$	
$c_{1,t}$	0.000	-(0.017)	0.045[c]	(4.246)	0.005	(0.491)	-0.012	-(1.227)
$c_{2,t}$	-0.131[c]	-(7.895)	-0.111[c]	-(6.663)	-0.081[c]	-(4.879)	-0.129[c]	-(8.006)
$c_{3,t}$	0.019[b]	(1.969)	0.016	(1.633)	-0.014	-(1.513)	0.012	(1.341)
	$c_{3,t-1}$		$c_{3,t-2}$		$c_{3,t-3}$		$c_{3,t-4}$	
$c_{1,t}$	0.183[c]	(9.894)	0.085[c]	(4.441)	0.046 [c]	(2.386)	-0.006	-(0.324)
$c_{2,t}$	0.401[c]	(13.669)	0.273[c]	(8.969)	0.028	(0.917)	0.016	(0.538)
$c_{3,t}$	-0.030[a]	-(1.772)	-0.044[b]	-(2.541)	-0.055[c]	-(3.107)	-0.126[c]	-(7.206)
	α							
$c_{1,t}$	0.000	-(0.002)						
$c_{2,t}$	0.000	-(0.003)						
$c_{3,t}$	0.000	-(0.001)						

Table 4-3: Spillovers in liquidity across regions in sub-periods

This table shows the VAR estimation results. Bonds are sorted into three portfolios based on their region of issuance. Subscript 1 stands for Asia, 2 for Europe and 3 for Latin America. The daily liquidity shocks, c_i, are computed using an AR(4) process of percentage bid/ask spread and they are market-value weighted. The VAR system of Equation (4.11) is estimated with J = 4 days for four sub-periods, 1994-1997, 1998-2001, 2002-2005 and 2006-2010 (January). The column variables are dependent variables. t-statistics are in the parentheses. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively. To save spaces, the intercept is not reported here.

1994-1997

	$c_{1,t-1}$		$c_{1,t-2}$		$c_{1,t-3}$		$c_{1,t-4}$	
$c_{1,t}$	-0.185[c]	-(5.260)	-0.080[b]	-(2.259)	-0.021	-(0.587)	0.020	(0.582)
$c_{2,t}$	-0.089[a]	-(1.920)	0.112[b]	(2.397)	0.065	(1.389)	0.019	(0.414)
$c_{3,t}$	-0.051[a]	-(1.656)	0.070[b]	(2.282)	0.002	(0.071)	-0.008	-(0.262)
	$c_{2,t-1}$		$c_{2,t-2}$		$c_{2,t-3}$		$c_{2,t-4}$	
$c_{1,t}$	-0.057[b]	-(2.032)	-0.025	-(0.899)	-0.082[c]	-(2.959)	0.045[a]	(1.648)
$c_{2,t}$	-0.104[c]	-(2.807)	-0.194[c]	-(5.239)	-0.145[c]	-(3.982)	-0.081[b]	-(2.288)
$c_{3,t}$	0.034	(1.409)	-0.031	-(1.277)	-0.087[c]	-(3.604)	0.027	(1.133)
	$c_{3,t-1}$		$c_{3,t-2}$		$c_{3,t-3}$		$c_{3,t-4}$	
$c_{1,t}$	0.372[c]	(8.564)	0.282[c]	(6.009)	0.161[c]	(3.280)	0.007	(0.153)
$c_{2,t}$	0.486[c]	(8.506)	0.435[c]	(7.023)	0.192[c]	(2.981)	-0.071	-(1.144)
$c_{3,t}$	-0.028	-(0.733)	0.039	(0.963)	-0.042	-(0.976)	-0.167[c]	-(4.061)

1998-2001

	$c_{1,t-1}$		$c_{1,t-2}$		$c_{1,t-3}$		$c_{1,t-4}$	
$c_{1,t}$	-0.056[a]	-(1.723)	-0.048	-(1.491)	0.073[b]	(2.333)	0.023	(0.734)
$c_{2,t}$	0.328[c]	(4.157)	0.312[c]	(3.945)	-0.037	-(0.488)	0.207[c]	(2.708)
$c_{3,t}$	0.077[c]	(1.996)	0.026	(0.670)	0.014	(0.371)	0.144[c]	(3.862)
	$c_{2,t-1}$		$c_{2,t-2}$		$c_{2,t-3}$		$c_{2,t-4}$	
$c_{1,t}$	-0.023[a]	-(1.791)	0.041[c]	(3.080)	0.027[b]	(2.052)	-0.029[b]	-(2.260)
$c_{2,t}$	-0.197[c]	-(6.152)	-0.108[c]	-(3.332)	-0.092[c]	-(2.836)	-0.178[c]	-(5.687)
$c_{3,t}$	0.012	(0.793)	0.036[b]	(2.280)	0.021	(1.319)	0.016	(1.029)
	$c_{3,t-1}$		$c_{3,t-2}$		$c_{3,t-3}$		$c_{3,t-4}$	
$c_{1,t}$	0.086[c]	(3.137)	0.013	(0.472)	0.022	(0.784)	0.021	(0.764)
$c_{2,t}$	0.389[c]	(5.830)	0.243[c]	(3.560)	-0.050	-(0.723)	0.085	(1.243)
$c_{3,t}$	-0.074[b]	-(2.282)	-0.102[c]	-(3.061)	-0.087[c]	-(2.586)	-0.105[c]	-(3.127)

2002-2005

	$c_{1,t-1}$		$c_{1,t-2}$		$c_{1,t-3}$		$c_{1,t-4}$	
$c_{1,t}$	-0.231[c]	-(7.218)	-0.160[c]	-(4.880)	-0.128[c]	-(3.961)	-0.069[b]	-(2.169)
$c_{2,t}$	-0.049	-(0.847)	-0.001	-(0.023)	-0.162[c]	-(2.771)	-0.058	-(1.021)
$c_{3,t}$	-0.016	-(0.306)	-0.008	-(0.140)	-0.043	-(0.794)	-0.026	-(0.484)
	$c_{2,t-1}$		$c_{2,t-2}$		$c_{2,t-3}$		$c_{2,t-4}$	
$c_{1,t}$	0.056[c]	(3.140)	0.040[b]	(2.238)	0.009	(0.510)	0.036[b]	(2.007)
$c_{2,t}$	-0.126[c]	-(3.899)	-0.160[c]	-(4.894)	0.022	(0.685)	-0.055[a]	-(1.694)
$c_{3,t}$	0.044	(1.477)	0.033	(1.103)	-0.018	-(0.596)	0.010	(0.346)
	$c_{3,t-1}$		$c_{3,t-2}$		$c_{3,t-3}$		$c_{3,t-4}$	
$c_{1,t}$	0.035[a]	(1.808)	0.046[b]	(2.384)	-0.005	-(0.286)	-0.014	-(0.750)
$c_{2,t}$	0.147[c]	(4.224)	0.102[c]	(2.915)	-0.039	-(1.122)	0.003	(0.100)
$c_{3,t}$	0.054[a]	(1.693)	-0.087[c]	-(2.695)	0.030	(0.939)	-0.139[c]	-(4.344)

2006-2010 (January)

	$c_{1,t-1}$		$c_{1,t-2}$		$c_{1,t-3}$		$c_{1,t-4}$	
$c_{1,t}$	0.107[c]	(3.282)	0.030	(0.924)	-0.075[b]	-(2.333)	0.058[a]	(1.841)
$c_{2,t}$	0.090[c]	(3.509)	0.025	(0.962)	0.003	(0.107)	0.088[c]	(3.519)
$c_{3,t}$	0.024	(1.455)	0.003	(0.160)	0.018	(1.118)	0.066[c]	(4.162)
	$c_{2,t-1}$		$c_{2,t-2}$		$c_{2,t-3}$		$c_{2,t-4}$	
$c_{1,t}$	0.186[c]	(4.446)	0.174[c]	(4.102)	0.030	(0.732)	-0.067[a]	-(1.670)
$c_{2,t}$	0.150[c]	(4.562)	0.012	(0.373)	-0.045	-(1.379)	-0.081[c]	-(2.579)
$c_{3,t}$	0.036[a]	(1.720)	0.016	(0.780)	-0.050[b]	-(2.429)	0.003	(0.147)
	$c_{3,t-1}$		$c_{3,t-2}$		$c_{3,t-3}$		$c_{3,t-4}$	
$c_{1,t}$	0.265[c]	(3.986)	0.160[b]	(2.358)	0.141[b]	(2.008)	-0.097	-(1.400)
$c_{2,t}$	0.313[c]	(5.960)	0.456[c]	(8.485)	0.134[b]	(2.412)	0.093[a]	(1.698)
$c_{3,t}$	-0.029	-(0.877)	0.057	(1.667)	0.051	(1.442)	-0.038	-(1.106)

4.5.2 Liquidity and return spillover hypothesis

Next, we examine whether liquidity commonality is associated with return commonality. According to the Idiosyncratic Liquidity Hypothesis (ILH), if idiosyncratic liquidity shocks are important, we should find that the lead and lag patterns in returns and those in liquidity shocks are similar. For the test, we extend the VAR model of Equation (4.11) to include innovations in return, r_i, in testing the lead/lag relationship between liquidity and returns. The modified VAR can be rewritten as

$$
\begin{aligned}
c_{1,t} &= \alpha_1 + \sum_{t=1}^{J} C_{t-j}\Phi_{1,j}^{C} + \sum_{j=1}^{J} R_{t-j}\Phi_{1,j}^{R} + \varepsilon_{1,t}, \\
c_{2,t} &= \alpha_2 + \sum_{j=1}^{J} C_{t-j}\Phi_{2,j}^{C} + \sum_{j=1}^{J} R_{t-j}\Phi_{2,j}^{R} + \varepsilon_{2,t}, \\
c_{3,t} &= \alpha_3 + \sum_{j=1}^{J} C_{t-j}\Phi_{3,j}^{C} + \sum_{j=1}^{J} R_{t-j}\Phi_{3,j}^{R} + \varepsilon_{3,t}, \\
r_{1,t} &= \kappa_1 + \sum_{j=1}^{J} C_{t-j}\Psi_{1,j}^{C} + \sum_{j=1}^{J} R_{t-j}\Psi_{1,j}^{R} + \mu_{1,t}, \\
r_{2,t} &= \kappa_2 + \sum_{j=1}^{J} C_{t-j}\Psi_{2,j}^{C} + \sum_{j=1}^{J} R_{t-j}\Psi_{2,j}^{R} + \mu_{2,t}, \\
r_{3,t} &= \kappa_3 + \sum_{j=1}^{J} C_{t-j}\Psi_{3,j}^{C} + \sum_{j=1}^{J} R_{t-j}\Psi_{3,j}^{R} + \mu_{3,t},
\end{aligned}
\tag{4.12}
$$

where

$$
\begin{aligned}
C_{t-j} &= \begin{bmatrix} c_{1,t-j} & c_{2,t-j} & c_{3,t-j} \end{bmatrix}, \\
R_{t-j} &= \begin{bmatrix} r_{1,t-j} & r_{2,t-j} & r_{3,t-j} \end{bmatrix}, \\
\Phi_{k,j}^{C} &= \begin{bmatrix} \phi_{k,j}^{c_1} & \phi_{k,j}^{c_2} & \phi_{k,j}^{c_3} \end{bmatrix}', \\
\Phi_{k,j}^{R} &= \begin{bmatrix} \phi_{k,j}^{r_1} & \phi_{k,j}^{r_2} & \phi_{k,j}^{r_3} \end{bmatrix}', \\
\Psi_{k,j}^{C} &= \begin{bmatrix} \psi_{k,j}^{c_1} & \psi_{k,j}^{c_2} & \psi_{k,j}^{c_3} \end{bmatrix}', \\
\Psi_{k,j}^{R} &= \begin{bmatrix} \psi_{k,j}^{r_1} & \psi_{k,j}^{r_2} & \psi_{k,j}^{r_3} \end{bmatrix}',
\end{aligned}
$$

where $r_{1,t}$, $r_{2,t}$ and $r_{3,t}$ are the innovations in returns as computed in Section 4.4.3 at time t of portfolios of Asian, European and Latin American bonds respectively. The capital letter R represents row vectors of lag values (lag-j subscripts). Ψ is a 3x1 (scalar) parameter for vectors of coefficients. Scalar κ is intercepts. μ_t is error terms. The other notations are the same as in Equation (4.11).

The results in Table 4-4 are consistent with those of Table 4-2 in terms of liquidity transmission within regions. Liquidity spills over from bonds issued in Latin America to those issued in developing Asian and European countries strongly and significantly. In most of the significant cases, the lagged liquidity shock, c_{t-j}, is positively associated with the contemporaneous return, r_t. This means that investors demand higher returns if a bond has higher contemporaneous liquidity shocks. Consistent with previous studies, for example, by Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996), we find that liquidity has a positive effect on required returns. Interestingly, these effects are also transmitted across regions. In addition, when experiencing a positive return shock, the liquidity is expected to improve in the next period (negative coefficients of lagged r_{t-j} for c_t).

The same pattern of lead/lag occurs in returns as in liquidity shocks, in the sense that we observe a strong positive lead/lag in returns from the Asian bond portfolio to Europe ($r_{1,t-j} \rightarrow r_{2,t}$) and from Latin America to Asia and Europe ($r_{3,t-j} \rightarrow r_{1,t}$ and $r_{3,t-j} \rightarrow r_{2,t}$), but not the other way around. The story here is in line with the Idiosyncratic Liquidity Hypothesis, where a return correlation is necessary for liquidity spillovers to be caused by idiosyncratic liquidity shock.

Table 4-4: Spillovers in liquidity and returns across regions

This table shows the VAR estimation results. Bonds are sorted into three portfolios based on their region of issuance. Subscript 1 stands for Asia, 2 for Europe and 3 for Latin America. The daily liquidity shocks, c_i, are computed using an AR(4) process of percentage bid/ask spread and they are market-value weighted. The return shocks, r_i, are also estimated using an AR(4) process. The VAR system of Equation (4.12) is estimated with J = 4 days for a whole sample period, 31 December 1994 to 31 January 2010. The column variables are dependent variables. t-statistics are in the parentheses. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively. To save spaces, the intercept is not reported here.

	$c_{1,t-1}$		$c_{1,t-2}$		$c_{1,t-3}$		$c_{1,t-4}$	
$c_{1,t}$	-0.089[c]	-(5.154)	-0.046[c]	-(2.649)	-0.023	-(1.330)	0.022	(1.277)
$c_{2,t}$	0.068[b]	(2.470)	0.111[c]	(4.025)	0.008	(0.302)	0.090[c]	(3.327)
$c_{3,t}$	-0.015	-(0.938)	0.034[b]	(2.166)	0.001	(0.051)	0.036[b]	(2.381)
$r_{1,t}$	0.059	(0.779)	0.050	(0.673)	0.241[c]	(3.241)	-0.095	-(1.297)
$r_{2,t}$	0.311[a]	(1.803)	0.268	(1.563)	-0.214	-(1.257)	-0.470[c]	-(2.792)
$r_{3,t}$	0.625[c]	(4.121)	0.018	(0.116)	-0.109	-(0.727)	-0.127	-(0.859)
	$c_{2,t-1}$		$c_{2,t-2}$		$c_{2,t-3}$		$c_{2,t-4}$	
$c_{1,t}$	-0.028[c]	-(2.649)	0.031[c]	(2.906)	-0.006	-(0.578)	-0.022[b]	-(2.146)
$c_{2,t}$	-0.162[c]	-(9.649)	-0.149[c]	-(8.830)	-0.096[c]	-(5.754)	-0.140[c]	-(8.605)
$c_{3,t}$	-0.003	-(0.295)	0.005	(0.501)	-0.021[b]	-(2.203)	0.009	(1.029)
$r_{1,t}$	0.102[b]	(2.220)	-0.141[c]	-(3.055)	0.018	(0.406)	0.050	(1.141)
$r_{2,t}$	0.258[b]	(2.459)	0.081	(0.765)	0.173[a]	(1.661)	-0.408[c]	-(4.029)
$r_{3,t}$	0.198[b]	(2.150)	0.025	(0.274)	0.303[c]	(3.327)	-0.265[c]	-(2.988)
	$c_{3,t-1}$		$c_{3,t-2}$		$c_{3,t-3}$		$c_{3,t-4}$	
$c_{1,t}$	0.109[c]	(5.162)	0.014	(0.623)	0.013	(0.589)	-0.035[a]	-(1.651)
$c_{2,t}$	0.260[c]	(7.674)	0.165[c]	(4.748)	-0.069[b]	-(1.984)	-0.020	-(0.574)
$c_{3,t}$	-0.167[c]	-(8.716)	-0.123[c]	-(6.265)	-0.107[c]	-(5.398)	-0.164[c]	-(8.490)
$r_{1,t}$	-0.061	-(0.665)	0.092	(0.970)	0.262[c]	(2.767)	-0.018	-(0.196)
$r_{2,t}$	-0.060	-(0.283)	-0.085	-(0.394)	0.576[c]	(2.652)	0.143	(0.675)
$r_{3,t}$	-0.018	-(0.095)	0.490[c]	(2.576)	0.933[c]	(4.891)	-0.119	-(0.638)
	$r_{1,t-1}$		$r_{1,t-2}$		$r_{1,t-3}$		$r_{1,t-4}$	
$c_{1,t}$	-0.021[c]	-(4.725)	-0.011[b]	-(2.359)	-0.026[c]	-(5.617)	-0.009[b]	-(1.968)
$c_{2,t}$	0.012	(1.612)	-0.022[c]	-(2.987)	0.002	(0.235)	0.001	(0.122)
$c_{3,t}$	0.003	(0.760)	0.003	(0.719)	0.007[a]	(1.679)	-0.008[a]	-(1.898)
$r_{1,t}$	-0.055[c]	-(2.758)	0.017	(0.865)	0.029	(1.453)	-0.001	-(0.072)
$r_{2,t}$	0.154[c]	(3.397)	0.136[c]	(2.990)	0.124[c]	(2.723)	0.143[c]	(3.199)
$r_{3,t}$	0.072[a]	(1.805)	0.089[b]	(2.218)	0.052	(1.309)	0.117[c]	(2.996)
	$r_{2,t-1}$		$r_{2,t-2}$		$r_{2,t-3}$		$r_{2,t-4}$	
$c_{1,t}$	-0.006[b]	-(2.468)	-0.001	-(0.376)	-0.006[c]	-(2.787)	-0.009[c]	-(3.844)
$c_{2,t}$	-0.005	-(1.529)	-0.020[c]	-(5.474)	-0.014[c]	-(3.780)	-0.015[c]	-(4.243)
$c_{3,t}$	0.001	(0.275)	-0.002	-(1.147)	-0.005[c]	-(2.598)	-0.001	-(0.278)
$r_{1,t}$	-0.050[c]	-(5.103)	-0.007	-(0.711)	0.036[c]	(3.615)	0.000	(0.010)
$r_{2,t}$	-0.156[c]	-(6.985)	0.020	(0.887)	0.037	(1.632)	-0.055[b]	-(2.465)
$r_{3,t}$	-0.080[c]	-(4.073)	-0.002	-(0.125)	0.077[c]	(3.863)	-0.015	-(0.780)
	$r_{3,t-1}$		$r_{3,t-2}$		$r_{3,t-3}$		$r_{3,t-4}$	
$c_{1,t}$	-0.004	-(1.410)	-0.012[c]	-(3.951)	0.001	(0.306)	-0.001	-(0.434)
$c_{2,t}$	-0.021[c]	-(4.707)	-0.003	-(0.606)	-0.010[b]	-(2.222)	-0.001	-(0.218)
$c_{3,t}$	-0.026[c]	-(10.229)	-0.014[c]	-(5.394)	-0.008[c]	-(2.941)	-0.011[c]	-(4.336)
$r_{1,t}$	0.152[c]	(12.537)	0.026[b]	(2.057)	-0.031[b]	-(2.449)	-0.001	-(0.118)
$r_{2,t}$	0.250[c]	(8.967)	-0.022	-(0.745)	-0.054[a]	-(1.848)	0.011	(0.380)
$r_{3,t}$	0.062[b]	(2.537)	0.034	(1.335)	0.004	(0.159)	-0.025	-(1.009)

4.5.3 Liquidity and volatility spillover hypothesis

We now examine whether the Systematic Liquidity Hypothesis (SLH) may also hold, under which contemporaneous liquidity and volatility of informationally-efficient assets (large bonds) should determine the future liquidity and volatility of informationally-passive assets (small bonds) rather than their returns. If SLH is relevant in explaining liquidity spillovers, then we should observe consistent patterns of spillovers in liquidity and volatility. To test this hypothesis, we include the innovations in volatility, $vol_{i,}$ in the VAR system of Equation (4.11) resulting in the following system:

$$
\begin{aligned}
c_{1,t} &= \alpha_1 + \sum_{t=1}^{J} C_{t-j}\Phi_{1,j}^{C} + \sum_{j=1}^{J} VOL_{t-j}\Phi_{1,j}^{VOL} + \varepsilon_{1,t}, \\
c_{2,t} &= \alpha_2 + \sum_{j=1}^{J} C_{t-j}\Phi_{2,j}^{C} + \sum_{j=1}^{J} VOL_{t-j}\Phi_{2,j}^{VOL} + \varepsilon_{2,t}, \\
c_{3,t} &= \alpha_3 + \sum_{j=1}^{J} C_{t-j}\Phi_{3,j}^{C} + \sum_{j=1}^{J} VOL_{t-j}\Phi_{3,j}^{VOL} + \varepsilon_{3,t}, \\
vol_{1,t} &= \lambda_1 + \sum_{j=1}^{J} C_{t-j}\Theta_{1,j}^{C} + \sum_{j=1}^{J} VOL_{t-j}\Theta_{1,j}^{VOL} + \nu_{1,t}, \\
vol_{2,t} &= \lambda_2 + \sum_{j=1}^{J} C_{t-j}\Theta_{2,j}^{C} + \sum_{j=1}^{J} VOL_{t-j}\Theta_{2,j}^{VOL} + \nu_{2,t}, \\
vol_{3,t} &= \lambda_3 + \sum_{j=1}^{J} C_{t-j}\Theta_{3,j}^{C} + \sum_{j=1}^{J} VOL_{t-j}\Theta_{3,j}^{VOL} + \nu_{3,t},
\end{aligned}
\tag{4.13}
$$

where

$$
\begin{aligned}
C_{t-j} &= \left[c_{1,t-j} \quad c_{2,t-j} \quad c_{3,t-j} \right], \\
VOL_{t-j} &= \left[vol_{1,t-j} \quad vol_{2,t-j} \quad vol_{3,t-j} \right], \\
\Phi_{k,j}^{C} &= \left[\phi_{k,j}^{c_1} \quad \phi_{k,j}^{c_2} \quad \phi_{k,j}^{c_3} \right]', \\
\Phi_{k,j}^{VOL} &= \left[\phi_{k,j}^{vol_1} \quad \phi_{k,j}^{vol_2} \quad \phi_{k,j}^{vol_3} \right]', \\
\Theta_{k,j}^{C} &= \left[\theta_{k,j}^{c_1} \quad \theta_{k,j}^{c_2} \quad \theta_{k,j}^{c_3} \right]', \\
\Theta_{k,j}^{VOL} &= \left[\theta_{k,j}^{vol_1} \quad \theta_{k,j}^{vol_2} \quad \theta_{k,j}^{vol_3} \right]',
\end{aligned}
$$

where $vol_{1,t}$, $vol_{2,t}$ and $vol_{3,t}$ are the innovations in volatility as computed in Section 4.4.3 at time t of portfolios of Asian, European and Latin American bonds respectively. The capital letter *VOL* represents row vectors of lag values (lag-j subscripts). Θ a is a 3x1 (scalar) parameter for vectors of coefficients. Scalar λ is intercepts. ν_t is error terms. The other notations are the same as in Equation (4.11).

Again, in Table 4-5 we find consistent and significant patterns in liquidity transmission across regions in the same way as those found in Tables 4-2 and 4-4. Liquidity shocks are transmitted 1) from bonds in Latin America to those in Asia and Europe and 2) from bonds in Asia to those in Europe. The lead/lag patterns in volatility across regions are the same as for those in liquidity. These observed liquidity and volatility commonalities are in agreement with the Systematic Liquidity Hypothesis (SLH).[103] More specifically, if liquidity of a bond issued in one region is affected more by the liquidity of a bond issued in another region, then the pattern of volatility movement will be the same as that of liquidity.

Another significant relation is that positive lagged volatility innovations are followed by higher liquidity shocks. Intuitively, an increase in volatility poses higher risks, which need to be compensated directly through a higher bid/ask spread to compensate a dealer for holding less than fully diversified portfolios. As expected, this effect is more pronounced within regions rather than across regions.

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[103] For a robustness test, we also include all innovations in illiquidity cost, returns and volatility in the VAR system at the same time and the results are essentially the same as reported before. Therefore, to save spaces, we do not report the results here.

Table 4-5: Spillovers in liquidity and volatility across regions

This table shows the VAR estimation results. Bonds are sorted into three portfolios based on their region of issuance. Subscript 1 stands for Asia, 2 for Europe and 3 for Latin America. The daily liquidity shocks, c_i, are computed using an AR(4) process of percentage bid/ask spread and they are market-value weighted. The volatility shocks, vol_i, are also estimated using an AR(4) process. The VAR system of Equation (4.13) is estimated with J = 4 days for a whole sample period, 31 December 1994 to 31 January 2010. The column variables are dependent variables. t-statistics are in the parentheses. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively. To save spaces, the intercept is not reported here.

	$c_{1,t-1}$		$c_{1,t-2}$		$c_{1,t-3}$		$c_{1,t-4}$	
$c_{1,t}$	-0.053[c]	-(3.200)	-0.030[a]	-(1.806)	0.001	(0.038)	0.036[b]	(2.176)
$c_{2,t}$	0.085[c]	(3.225)	0.139[c]	(5.276)	0.019	(0.742)	0.090[c]	(3.481)
$c_{3,t}$	-0.005	-(0.349)	0.020	(1.292)	-0.001	-(0.079)	0.047[c]	(3.143)
$vol_{1,t}$	-0.013	-(1.023)	0.014	(1.054)	0.019	(1.426)	0.083[c]	(6.474)
$vol_{2,t}$	-0.048[a]	-(1.705)	0.033	(1.173)	-0.052[a]	-(1.883)	0.197[c]	(7.220)
$vol_{3,t}$	0.001	(0.024)	0.026	(1.124)	0.003	(0.139)	0.158[c]	(7.067)
	$c_{2,t-1}$		$c_{2,t-2}$		$c_{2,t-3}$		$c_{2,t-4}$	
$c_{1,t}$	-0.006	-(0.587)	0.042[c]	(3.939)	0.003	(0.277)	-0.019[a]	-(1.890)
$c_{2,t}$	-0.150[c]	-(8.921)	-0.132[c]	-(7.788)	-0.083[c]	-(4.966)	-0.144[c]	-(8.853)
$c_{3,t}$	0.018[a]	(1.913)	0.017[a]	(1.758)	-0.013	-(1.333)	0.004	(0.425)
$vol_{1,t}$	-0.015[a]	-(1.736)	0.009	(1.096)	0.007	(0.852)	-0.007	-(0.908)
$vol_{2,t}$	-0.010	-(0.561)	0.007	(0.372)	0.009	(0.514)	-0.015	-(0.858)
$vol_{3,t}$	-0.040[c]	-(2.751)	0.016	(1.121)	-0.024	-(1.631)	-0.032[b]	-(2.259)
	$c_{3,t-1}$		$c_{3,t-2}$		$c_{3,t-3}$		$c_{3,t-4}$	
$c_{1,t}$	0.151[c]	(7.540)	0.051[b]	(2.460)	0.036[a]	(1.738)	0.003	(0.154)
$c_{2,t}$	0.309[c]	(9.703)	0.160[c]	(4.878)	-0.042	-(1.271)	-0.033	-(1.010)
$c_{3,t}$	-0.094[c]	-(5.140)	-0.094[c]	-(4.980)	-0.071[c]	-(3.775)	-0.150[c]	-(8.091)
$vol_{1,t}$	0.053[c]	(3.322)	0.051[c]	(3.112)	0.001	(0.041)	-0.004	-(0.271)
$vol_{2,t}$	0.120[c]	(3.553)	0.111[c]	(3.201)	0.031	(0.891)	0.000	(0.009)
$vol_{3,t}$	0.187[c]	(6.787)	0.172[c]	(6.047)	0.075[c]	(2.642)	0.046	(1.625)
	$vol_{1,t-1}$		$vol_{1,t-2}$		$vol_{1,t-3}$		$vol_{1,t-4}$	
$c_{1,t}$	0.101[c]	(4.269)	0.109[c]	(4.578)	0.123	(5.138)	0.050[b]	(2.080)
$c_{2,t}$	-0.002	-(0.042)	0.148[c]	(3.902)	0.036	(0.949)	0.054	(1.433)
$c_{3,t}$	-0.002	-(0.116)	0.079[c]	(3.640)	0.011	(0.526)	0.074[c]	(3.372)
$vol_{1,t}$	-0.045[b]	-(2.437)	-0.019	-(0.990)	-0.016	-(0.850)	0.048[b]	(2.539)
$vol_{2,t}$	0.203[c]	(5.127)	-0.023	-(0.571)	0.009	(0.220)	0.196[c]	(4.874)
$vol_{3,t}$	-0.052	-(1.600)	-0.082[b]	-(2.489)	-0.077	-(2.342)	0.121[c]	(3.664)
	$vol_{2,t-1}$		$vol_{2,t-2}$		$vol_{2,t-3}$		$vol_{2,t-4}$	
$c_{1,t}$	-0.019	-(1.557)	-0.008	-(0.641)	0.001	(0.073)	0.019	(1.530)
$c_{2,t}$	0.034[a]	(1.740)	0.064[c]	(3.291)	-0.007	-(0.359)	0.035[a]	(1.800)
$c_{3,t}$	-0.015	-(1.371)	-0.026[b]	-(2.368)	-0.011	-(0.953)	0.015	(1.319)
$vol_{1,t}$	-0.001	-(0.107)	-0.021[b]	-(2.222)	-0.013	-(1.339)	-0.003	-(0.288)
$vol_{2,t}$	-0.082[c]	-(4.007)	-0.036[a]	-(1.771)	-0.022	-(1.050)	-0.026	-(1.280)
$vol_{3,t}$	0.005	(0.287)	0.044[c]	(2.647)	0.008	(0.467)	-0.009	-(0.537)
	$vol_{3,t-1}$		$vol_{3,t-2}$		$vol_{3,t-3}$		$vol_{3,t-4}$	
$c_{1,t}$	0.026[a]	(1.644)	0.040[c]	(2.546)	-0.021	-(1.318)	-0.059[c]	-(3.817)
$c_{2,t}$	0.096[c]	(3.906)	0.080[c]	(3.209)	0.071[c]	(2.850)	-0.007	-(0.286)
$c_{3,t}$	0.108[c]	(7.652)	0.068[c]	(4.770)	-0.001	-(0.090)	-0.005	-(0.344)
$vol_{1,t}$	0.047[c]	(3.852)	0.017	(1.341)	0.018	(1.453)	0.011	(0.913)
$vol_{2,t}$	0.045[a]	(1.739)	0.021	(0.779)	0.009	(0.350)	0.012	(0.476)
$vol_{3,t}$	-0.045[c]	-(2.119)	-0.072[c]	-(3.347)	-0.020	-(0.952)	-0.033	-(1.555)

To summarize this section, we find that there exist liquidity commonalities across regions and patterns of liquidity transmission are consistent with those of both returns and volatility. Our empirical evidence supports both ILH and SLH, i.e., the synchronized pattern of liquidity dynamics is caused by both systematic and idiosyncratic shocks to liquidity. Indeed, explanations of liquidity spillovers by these two hypotheses are not necessarily competing, but they are complementary. In the next section, we will look more closely at the significance of the causal relation between commonality in liquidity versus that in returns and volatility in order to examine the relative degree of importance of the ILH and SLH for liquidity spillovers.

4.6 Importance of Idiosyncratic versus Systematic Shocks

From previous section's results, we know that liquidity spillovers coincide with both bond return commonalities and bond volatility commonalities. However, we do not know which is more important. To find out, we need to develop precise commonality measures for liquidity, returns, and volatility. Following Roll (1988), Morck, Yeung and Yu (2000) and Karolyi, Lee and Dijk (2009), we use the R^2 of a regression of individual bond portfolios on the overall market as a measure of the degree to which liquidity, returns and volatility of bond portfolios move together, i.e., we use the R^2 as our measure of commonality in liquidity, returns and volatility. In constructing our commonality measures, we would like to separate-out the effects of liquidity, returns and volatility on one another. Therefore, we first run a filtering regression on our daily data for each country bond portfolio as follows:

$$
\begin{aligned}
C_t^i &= \alpha_{i,c}^c C_{t-1}^i + \alpha_{i,c}^r R_{t-1}^i + \alpha_{i,c}^{vol} VOL_{t-1}^i + \beta_{i,c}^c C_{t-1}^M + \beta_{i,c}^r R_{t-1}^M + \beta_{i,c}^{vol} VOL_{t-1}^M + \sum_n^5 \lambda_{i,c}^D D_n + \varepsilon_{t,c}^i, \\
R_t^i &= \alpha_{i,r}^c C_{t-1}^i + \alpha_{i,r}^r R_{t-1}^i + \alpha_{i,r}^{vol} VOL_{t-1}^i + \beta_{i,r}^c C_{t-1}^M + \beta_{i,r}^r R_{t-1}^M + \beta_{i,r}^{vol} VOL_{t-1}^M + \sum_n^5 \lambda_{i,r}^D D_n + \varepsilon_{t,r}^i, \\
VOL_t^i &= \alpha_{i,vol}^c C_{t-1}^i + \alpha_{i,vol}^r R_{t-1}^i + \alpha_{i,vol}^{vol} VOL_{t-1}^i + \beta_{i,vol}^c C_{t-1}^M + \beta_{i,vol}^r R_{t-1}^M + \beta_{i,vol}^{vol} VOL_{t-1}^M + \sum_n^5 \lambda_{i,vol}^D D_n + \varepsilon_{t,vol}^i,
\end{aligned}
\tag{4.14}
$$

where C_t^i (R_t^i and VOL_t^i) is the daily bid/ask spread (return and volatility) of country i at date t as computed in Sections 4.4.1 and 4.4.2, superscript M stands for the aggregate emerging bond market and D_n denotes day-of-the-week dummy. In constructing the commonality measures, we use the residuals (ε_t^i) from the filtering regression of Equation (4.14) because of two reasons: 1) we control for any possible mechanistic relation between the underlying market liquidity, returns and volatility and 2) we include lagged variables to address the persistent nature in liquidity and volatility. These estimated residuals also reflect shocks or unexpected fluctuation in liquidity, returns and volatility. We are interested in the degree of association of these individual residuals with their market movements. Therefore, we derive the monthly commonality measures in liquidity (R^2_c), in returns (R^2_r) and in volatility (R^2_{vol}) by taking the R^2s from the following regression of residuals from Equation (4.14) on the aggregate residuals using daily data within a given month:

$$\begin{aligned} \hat{\varepsilon}^i_{t,c} &= a^i_c + \sum_{J=-1}^{1} b^i_{J,c}\hat{\varepsilon}^M_{t+J,c} + \mu^i_{t,c}, \\ \hat{\varepsilon}^i_{t,r} &= a^i_r + \sum_{J=-1}^{1} b^i_{J,r}\hat{\varepsilon}^M_{t+J,r} + \mu^i_{t,r}, \\ \hat{\varepsilon}^i_{t,vol} &= a^i_{vol} + \sum_{J=-1}^{1} b^i_{J,vol}\hat{\varepsilon}^M_{t+J,vol} + \mu^i_{t,vol}, \end{aligned} \tag{4.15}$$

where ε^M denotes the aggregate residual from Equation (4.14) with the market-value weighting of the residuals for all country bond portfolios excluding country *i*. Following Chordia, Roll and Subrahmanyam (2000) and Karolyi, Lee and Dijk (2009), the contemporaneous aggregate market residuals plus their one lead and one lag are included as regressors in Equation (4.15). The lead and lag help alleviate any spurious dependence in computing the commonality measures. R^2s are computed for every month, which has at least 10 days of observations. The commonality measures, or R^2s, always have values ranging from [0,1] and therefore should suffer less scaling effects.

4.6.1 Summary statistics: commonality measures

First of all, Table 4-6 provides summary statistics of market capitalization, yield to maturity, maturity, bid/ask spread, return and volatility for every country bond

Table 4-6: Summary of country/region bond portfolios' statistics at the end of 2009

Country/region	Market cap (billionU.S.$)	Market cap (% in total)	Yield to maturity (%)	Maturity (year)	2009's Avg. daily bid/ask spread (%)	2009's Avg. daily return (%)	2009's Avg. daily volatility (%)
Argentina	4.82	(1.41%)	10.85	22.12	1.83	0.36	3.38
Belize	0.41	(0.12%)	15.51	14.37	2.94	0.19	0.96
Brazil	43.27	(12.64%)	5.91	14.84	0.58	0.04	0.68
Bulgaria	1.53	(0.45%)	4.39	5.03	1.28	0.10	0.53
Chile	4.81	(1.41%)	4.56	9.31	1.48	0.05	0.73
China	6.05	(1.77%)	3.14	4.27	1.71	0.03	0.48
Colombia	12.74	(3.72%)	5.83	13.10	0.63	0.06	0.71
Croatia	1.63	(0.48%)	5.67	9.83	0.47	-1.78	2.96
Dominican Republic	0.71	(0.21%)	6.90	5.80	2.23	0.26	1.27
Ecuador	0.61	(0.18%)	10.53	5.94	2.49	0.32	1.75
Egypt	1.15	(0.34%)	0.76	1.51	2.17	0.05	0.27
El Salvador	3.94	(1.15%)	7.28	14.91	1.33	0.14	0.80
Gabon	0.95	(0.28%)	7.25	7.93	3.14	0.22	1.30
Georgia	0.51	(0.15%)	6.46	3.28	4.43	0.24	1.16
Ghana	0.88	(0.26%)	7.93	7.74	3.28	0.28	1.53
Hungary	1.53	(0.45%)	4.54	5.08	3.41	0.09	1.05
Indonesia	20.65	(6.03%)	6.15	13.53	1.83	0.16	1.41
Iraq	2.16	(0.63%)	8.51	14.28	3.34	0.28	1.65
Jamaica	0.45	(0.13%)	11.31	28.19	5.95	0.13	1.89
Kazakhstan	5.68	(1.66%)	6.83	5.95	2.44	0.21	1.31
Lebanon	10.60	(3.10%)	5.82	5.54	1.85	0.10	0.37
Malaysia	10.92	(3.19%)	4.72	6.75	0.92	0.05	0.49
Mexico	40.10	(11.72%)	5.86	14.33	0.78	0.05	0.89
Pakistan	1.24	(0.36%)	10.02	6.94	4.67	0.38	2.54
Panama	8.41	(2.46%)	5.78	16.17	0.84	0.09	0.59
Peru	8.99	(2.63%)	5.67	14.82	0.69	0.08	0.72
Philippines	27.08	(7.91%)	5.93	12.27	0.80	0.09	0.62
Poland	7.56	(2.21%)	4.51	6.76	1.76	0.05	0.70
Russia	36.72	(10.73%)	5.58	8.59	0.81	0.14	0.90
Serbia	1.08	(0.31%)	6.75	7.57	3.83	0.23	1.18
South Africa	5.51	(1.61%)	4.92	7.58	0.93	0.09	0.57
Sri Lanka	1.07	(0.31%)	6.03	3.92	2.52	0.23	1.58
Tunisia	1.51	(0.44%)	3.17	2.30	1.98	0.06	0.34
Turkey	34.27	(10.01%)	5.77	11.72	1.46	0.09	0.86
Ukraine	3.58	(1.05%)	12.34	4.32	3.06	0.32	2.15
Uruguay	5.86	(1.71%)	6.52	17.44	1.02	0.13	0.81
Venezuela	22.30	(6.51%)	13.98	13.71	1.48	0.20	1.87
Vietnam	1.00	(0.29%)	6.07	6.03	1.80	0.12	1.13
Africa Region	9.10	(2.66%)	5.35	6.49	1.71	0.11	0.48
Asia Region	80.35	(23.47%)	5.79	10.63	1.26	0.10	0.61
Europe Region	95.64	(27.94%)	5.80	8.95	1.37	0.12	0.71
Latin Region	157.20	(45.93%)	7.47	14.76	0.90	0.08	0.72
Total	342.30		6.71	11.98	1.15	0.10	0.57
Mean	9.01		6.84	9.84	2.06	0.10	1.16
Median	4.38		5.98	7.84	1.82	0.12	0.93

portfolio included in the EMBI at the end of 2009. The market value of overall aggregate bonds is 342 billion U.S. dollar. In terms of market capitalization, Brazilian bonds are the largest, being 12.64 per cent of the total. The average aggregate maturity is 11.98 years. Each country's bid/ask spread tends to co-move together with its return and volatility. Cross-sectional correlations of bid/ask spreads with respect to returns and volatility are 0.36 and 0.37 respectively. In 2009, the aggregate volatility of the emerging sovereign bond markets is about 9.01 ($0.57 \cdot 250^{0.5}$) per cent per annum.

Figure 4-7 depicts the average values of estimated liquidity, return and volatility commonalities (R^2_c, R^2_r and R^2_{vol}) computed from Equation (4.15) over the period from January 2000 to January 2010 across 23 countries from Asia, Europe and Latin America.[104] Uruguay has the highest average values of R^2_c, R^2_r and R^2_{vol} (42%, 53% and 57%). Besides Uruguay, another country that has high liquidity commonality is Dominican Republic. Both are Latin American nations. The figure also shows that the ranking of countries across the three commonality measures is consistent; many countries are in a similar ranking position in all three diagrams. The correlations and rank correlations (not tabulated) between the commonality measure are all more than 0.79 and 0.40 respectively. At the country level, this cross-sectional evidence again supports the view that liquidity, returns and volatility tend to move together.

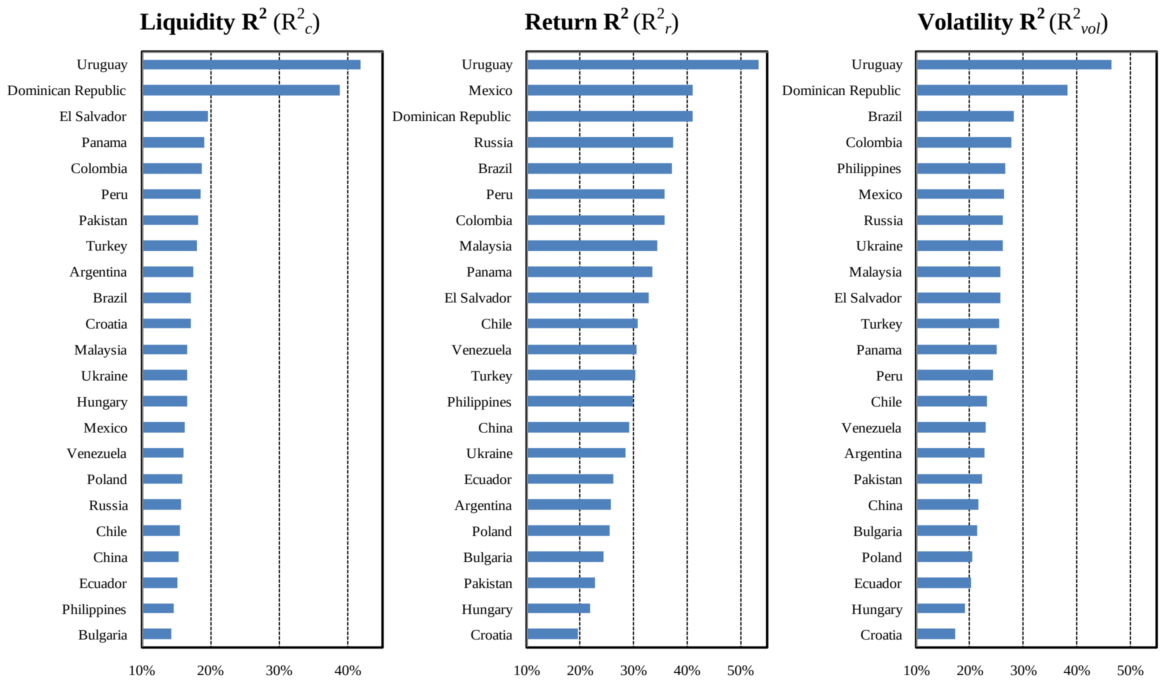
Our model in Section 4.3 suggests that both idiosyncratic and systematic liquidity shocks can cause liquidity commonality or liquidity spillovers, but they should relate to different patterns of return and volatility co-movements. If the commonality in liquidity

[104] For the sake of comparison, Figure 4-7 includes only countries, which have balanced data covering January 2000 to January 2010 (23 countries). All 35 countries are included in the cross-section (by country) and time-series (by region) analyses.

is caused by idiosyncratic shocks, we should observe consistent patterns in liquidity and returns. On the other hand, if the spillovers are induced by the systematic shocks, the coincidence of the liquidity and volatility commonality should be strong. We investigate these relations both in cross-section and time-series below.

Figure 4-7: Liquidity, return and volatility commonalities

This figure depicts the average monthly commonality in liquidity, returns, volatility (R^2_c, R^2_r and R^2_{vol}) of 23 countries, which all have balanced data from January 2000 to January 2010. For each country bond portfolio, R^2s are computed from monthly regressions of daily observations of illiquidity cost, returns and volatility on the lead, lag and contemporaneous aggregate market value of liquidity cost, returns and volatility respectively (see Equation (4.15) for more detail). Countries are sorted from high to low values of commonality measures.



4.6.2 Cross-section analysis of commonality measures (35 countries)

To analyze cross-country variations of commonality in liquidity, returns and volatility, we run cross-sectional regression of average liquidity commonality (R^2_c) on combinations of return and volatility (R^2_r and R^2_{vol}) in 35 countries across Asia, Europe and Latin America continents. Table 4-7 reports the results. In models 7.1 and 7.2,

Table 4-7: Cross-sectional regression of country bond portfolio's liquidity commonality on return and volatility commonalties

This table reports OLS estimation results of cross-sectional regression of the time-series average commonality in liquidity (R^2_c) on those in returns and volatility (R^2_r and R^2_{vol}) in 35 countries. Bonds are grouped by country of issuance and the grouping employs the market value weighting. The models are alternative cases of the following equation:

$$R^2_{c,i} = \alpha + \gamma_1 R^2_{r,i} + \gamma_2 R^2_{vol,i}.$$

t-statistics are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively. R^2 and Adjusted R^2 are reported in the last column.

Model	Constant	Explanatory variable: *Return commonality* (R^2_r)	Explanatory variable: *Volatility commonality* (R^2_{vol})	R^2 (adj-R^2)
7.1	0.090	0.368[a]		0.23
	(1.602)	(1.861)		(0.21)
7.2	0.023		0.706[c]	0.48
	(0.510)		(3.810)	(0.46)
7.3	0.020	-0.608	1.443[c]	0.60
	(0.590)	-(0.823)	(4.301)	(0.57)

where R^2_r and R^2_{vol} are entered in the regression as separate regressors, both commonalities are significantly and positively related to the liquidity commonality. Even though a different time interval (monthly data for commonality measures in this section as opposed to daily data in Section 4.5) is deployed, again results here are in line with our previous findings that a country, which has higher co-movement of return and volatility, experiences higher liquidity co-movement with the aggregate market liquidity, i.e., both ILH and SLH hold. However, when both R^2_r and R^2_{vol} are included in model 7.3 of Table 4-7, the impact of the R^2_r is no longer significant. The estimated coefficient on R^2_{vol} is still positive and significant. In fact, the inclusion of the R^2_r does not produce much improvement in terms of the adjusted R^2 compared to the case when just R^2_{vol} is entered in model 7.2 (0.46 and 0.57). In terms of economic significance, the impact of R^2_{vol} is also larger. From models 7.1 and 7.2, an increase of one standard deviation in R^2_{vol} is related to a rise in R^2_c by 4.54% (about 0.60 times of one cross-sectional standard deviation in R^2_c), whereas an increase of one standard deviation in R^2_r increases R^2_c by 2.88% (or 0.38 times of one cross-sectional standard deviation in R^2_c).

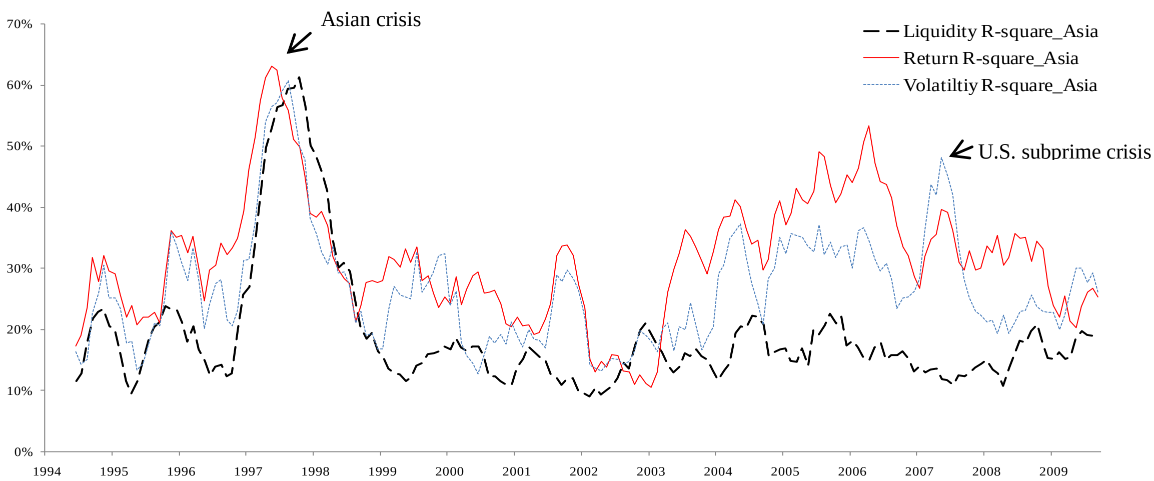
In general, the results suggest that commonality in liquidity is more associated with that in volatility (systematic liquidity shocks) than with that in returns (idiosyncratic liquidity shocks) in the cross-country analysis and the volatility effect on liquidity is more economically significant.

4.6.3 Time-series analysis of commonality measures (three regions)

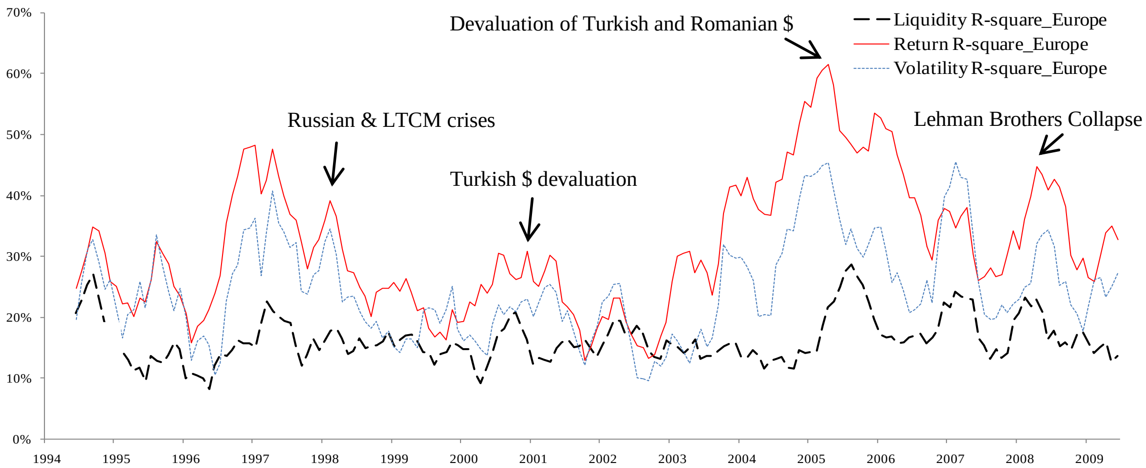
As in Section 4.5, using the market value weighing, we group our emerging bonds into three regions, Asia, Europe and Latin America, and compute regional measures of commonality in liquidity, returns and volatility from country measures following Equations (4.14) and (4.15). Figure 4-8 depicts the time-series of six-month moving average commonality measures in liquidity, returns and volatility for Asian, European and Latin American sovereign bond portfolios. Both within a region and across regions, they generally move in similar patterns. For Asian bonds, all three commonalities hit their peak in the mid 1997 at the onset of Asian Crisis. The Asian crisis appears to stimulate the liquidity, return and volatility commonalities in Europe and Latin America as well. The figure also indicates that all commonalities (and to a lesser extent, liquidity co-movement, R^2_c) vary markedly over time. An increase in these commonalities coincides with periods of global economic disorder such as the Mexican Peso devaluation of December 1994, the Asian Crisis of mid 1997, the Russian Ruble devaluation of August 1998, the LTCM crisis of September 1998, the Brazilian Real devaluation of January 1999, the Turkish Lira devaluation of February 2001, Argentina’s debt moratorium of December 2001, the Turkish and Romanian currency devaluation of early 2005, the U.S. subprime crisis of mid 2007 and the Lehman Brothers collapse of September 2008. In addition, the sharply-increased commonalities

Figure 4-8: Time-series of commonality measures by a region bond portfolio
This figure depicts the time-series of six-month moving average commonality measures in liquidity, returns and volatility for Asian, European, Latin American bond portfolios in Panels A, B and C respectively.

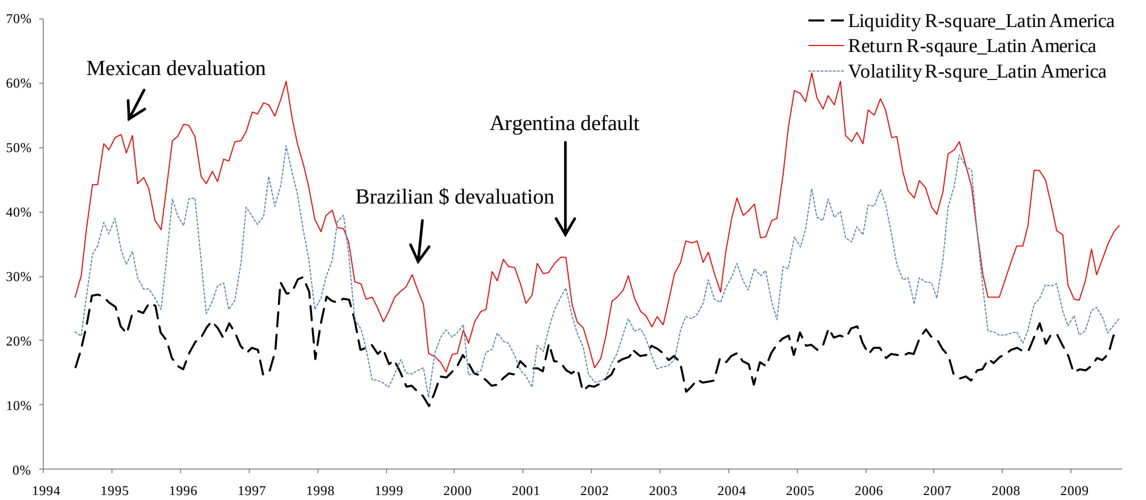
Panel A: Asian bond portfolio



Panel B: European bond portfolio



Panel C: Latin American bond portfolio



driven by such crises seem to spill over across regions, which is consistent with our previous empirical results using the Vector Autoregression (VAR) model in Section 4.5. Note that currency devaluation event is one of the important factors driving the commonality in all regions partly because our sample is U.S. dollar-denominated bonds traded mainly in the international community rather than in their own local markets.

In order to investigate whether idiosyncratic or systematic liquidity shocks are more important for commonality in liquidity over time, we run a time-series regression of commonality in liquidity (R^2_c) on those in returns and volatility (R^2_r and R^2_{vol}) in three regions, Asia, Europe and Latin America. When only R^2_r and R^2_{vol} are included as an explanatory variable, regression results in Table 4-8 always find a positive and significant relation between R^2_{vol} and R^2_c, but not between R^2_r and R^2_c. The finding is consistent across all regions. The results in all regressions are barely changed even if the relevant one-month lagged variables ($R^2_{c,t-1}$, $R^2_{r,t-1}$ and $R^2_{vol,t-1}$) are added-in. The only significant variable is the lag of liquidity commonality for the Asian region, indicating that Asia encounters more persistent commonality in liquidity. In the last row of Table 4-8, we run a regression of the commonality in aggregate market liquidity on those in returns and volatility. The coefficients on R^2_{vol} are still positive and significant. As before, we have positive coefficients on R^2_r, but they are not significant in every specification. The economic significance of the effects of the R^2_{vol} on R^2_c is also stronger. For example, in the case of the first model of the aggregate market, one standard deviation increase in R^2_{vol} is associated with an increase in the R^2_c by 1.94% (or 0.27 times of one time-series standard deviation in R^2_c) while an increase of one standard deviation in R^2_r increases R^2_c by 0.89% (or 0.12 times of one standard deviation in R^2_c).

Table 4-8: Time-series regression of region bond portfolio's liquidity commonality on return and volatility commonalities

This table reports OLS estimation results of time-series regression of the commonality in liquidity (R^2_c) on those in returns and volatility (R^2_r and R^2_{vol}) in three regions, Asia, Europe and Latin America and the aggregate market. Bonds are grouped by region of issuance and the grouping employs the market value weighting. The models are alternative cases of the following equation:

$$R^2_{c,t} = \phi + \omega_1 R^2_{r,t} + \omega_2 R^2_{vol,t} + \omega_3 R^2_{c,t-1} + \omega_4 R^2_{r,t-1} + \omega_5 R^2_{vol,t}.$$

In some specification, lagged variables are included. t-statistics are reported in the parentheses. Significance at the 10%, 5% and 1% level is indicated by [a], [b]and [c] respectively. R^2 and Adjusted R^2 are reported in the last column.

Region	constant	R^2_r	R^2_{vol}	$R^2_{c,t-1}$	$R^2_{r,t-1}$	$R^2_{vol,t-1}$	R^2 (adj-R^2)
Asia	0.085[c]	0.070	0.087[c]				0.17
($R^2_{c, Asia}$)	(4.401)	(1.529)	(2.607)				(0.15)
	0.024	0.101	0.074[b]	0.522[c]	0.040	0.012	0.43
	(1.252)	(1.599)	(2.267)	(8.235)	(0.641)	(0.207)	(0.41)
Europe	0.120[c]	0.063	0.090[a]				0.08
($R^2_{c, Europe}$)	(9.378)	(1.289)	(1.926)				(0.07)
	0.113[c]	0.048	0.086[a]	0.071	0.041	-0.044	0.08
	(6.722)	(0.900)	(1.816)	(0.946)	(0.786)	-(0.927)	(0.06)
Latin America	0.135[c]	0.066	0.089[a]				0.08
($R^2_{c, Latin America}$)	(9.193)	(1.341)	(1.789)				(0.07)
	0.110[c]	0.029	0.090[a]	0.103	0.062	-0.014	0.10
	(5.748)	(0.549)	(1.809)	(1.403)	(1.166)	-(0.272)	(0.08)
Aggregate Market	0.128[c]	0.059	0.121[c]				0.14
($R^2_{c, Market}$)	(10.648)	(1.312)	(2.718)				(0.12)
	0.101[c]	0.014	0.127[c]	0.171[b]	0.059	-0.039	0.17
	(6.329)	(0.288)	(2.876)	(2.345)	(1.188)	-(0.853)	(0.15)

To summarize this section, both the cross-country and time-series analyses show that the relationship between R^2_{vol} and R^2_c is more pronounced than that between R^2_r and R^2_c. Its economic significance is also stronger. In other words, systematic liquidity shocks are more important than idiosyncratic liquidity shocks in explaining the transmission of liquidity in emerging U.S. dollar sovereign bonds during our sample period.

4.7 Conclusions

In contrast to previous studies that assume liquidity to be an exogenous factor, we develop a model of the dynamics of liquidity across securities. Our model differentiates between liquidity spillovers caused by idiosyncratic liquidity risks and those caused by systematic liquidity risks by relating them to spillovers in returns and in volatility respectively. The first explanation for liquidity spillovers is based on idiosyncratic liquidity shocks. If the two assets are correlated in returns and one asset is hit by this type of shock, there will be a concentration of trading in the other. This implies consistency of return and liquidity spillovers. An alternative explanation, which is more obvious, is that liquidity spillovers are due to the systematic liquidity shocks. It predicts that the lead and lag patterns in liquidity should be consistent with those in volatility, but not necessarily with those in returns. The model also shows that liquidity can be transmitted across assets even though there is (i) no information asymmetry, (ii) the same initial endowment for each investor and (iii) the same investors' expectation about future liquidity shocks.

The model is then applied to U.S. dollar sovereign bonds in 35 emerging markets, grouped into Asia, Europe and Latin America. The empirical results shows that liquidity spillovers are mainly from Latin America to other regions and they are both systematic and idiosyncratic in character. Therefore, systematic and idiosyncratic liquidity risks are not competing, but complementary explanations of liquidity spillovers and liquidity cannot be considered in isolation. Cross-section (across countries) and time-series (across regions) analyses find that systematic spillovers are more statistically and economically significant than idiosyncratic spillovers. It follows that the liquidity risk is related predominantly to systematic factors, which investors cannot easily diversify away.

Our demonstration that liquidity spillovers are not solely generated by return co-movement has important implications for financial market participants. Liquidity can adversely affect portfolio performance and swiftly cancel out diversification benefits. [105] Fund managers cannot perfectly diversify their international portfolios by just investing in bonds, which have low correlations in returns, because such bonds may have high liquidity co-movements. In addition, understanding the nature of liquidity spillovers helps market participants to be aware of the risk of their trading. Financial market regulators and central banks should acknowledge that liquidity formation in their local market can, at times, be more related to global or systematic factors than to their country-specific fundamentals. To prevent future liquidity crises, they should put more effort into monitoring the co-movement of volatility rather than that of returns. Moreover, the commonality in liquidity, returns and volatility increases sharply during periods of global economic crises and is transmitted among regions. Researchers should incorporate time-varying liquidity risk for a more realistic asset pricing model.

Though it is not this paper’s focus, a further cross-country study on why commonality varies across countries could be beneficial for policy makers, who would like to reduce the liquidity risk in their financial markets. Identifying the possible determinants of cross-country commonality, such as the level of economic and financial development,

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[105] The study that find the international diversification benefits includes De Santis and Gerard (1997), Korajczyk and Sadka (2004) and Lesmond, Schill and Zhou (2004).

investor sentiment, funding liquidity [106], institutional ownership [107], the role of institutional and foreign investors and the related regulatory issues, could be a direction for future research.

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[106] Brunnermeier and Pedersen (2008) define funding liquidity as the ease with which market makers can obtain funding.

[107] Kamara, Lou and Sadka (2008) find that the firm's cross-sectional commonality in liquidity increases with institutional ownership because institutional investing and index trading concentrate more in large-cap stocks than in small-cap stocks.

Appendix 4A: Proof of the Liquidity Spillover Model

With a negative utility function, Equation (4.2) can be rewritten as

$$\max_{x_{0,i}^{A,B}} E_0\{\max_{x_{t,i}^{A,B}} E_1[-\exp\{-a[w_{0,i} + x_{0,i}^A(\tilde{p}_1^A - \tilde{p}_0^A) + x_{1,i}^A(\tilde{v}^A + \tilde{\theta}_i^A - \tilde{p}_1^A) + x_{0,i}^B(\tilde{p}_1^B - \tilde{p}_0^B) + x_{1,i}^B(\tilde{v}^B + \tilde{\theta}_i^B - \tilde{p}_1^B)]\}]\}. \tag{4A.1}$$

Using a recursive method, investor i at time t = 1 maximizes the following utility function:

$$\max_{x_{t,i}^{A,B}} E_1[-\exp\{-a[w_{0,i} + x_{1,i}^A(\tilde{v}^A + \hat{\theta}_i^A - p_1^A) + x_{1,i}^B(\tilde{v}^B + \hat{\theta}_i^B - p_1^B)]\}]. \tag{4A.2}$$

Therefore, the first order conditions with respective to $x_{1,i}^A$ and $x_{1,i}^B$ are given by

$$\begin{aligned} &\bar{v}^A + \hat{\theta}_i^A - p_1^A - a\sigma_v^{2,A} x_{1,i}^A - a\rho_v^{A,B}\sigma_v^A\sigma_v^B x_{1,i}^B = 0, \\ &\bar{v}^B + \hat{\theta}_i^B - p_1^B - a\sigma_v^{2,B} x_{1,i}^B - a\rho_v^{A,B}\sigma_v^A\sigma_v^B x_{1,i}^A = 0. \end{aligned} \tag{4A.3}$$

The market clearing condition implies that

$$\sum\nolimits_{i=1}^M x_{1,i}^A = \sum\nolimits_{i=1}^M x_{1,i}^B = M. \tag{4A.4}$$

Note that $\hat{\theta}_M^A = \dfrac{\sum_{i=1}^M \hat{\theta}_i^A}{M} = \hat{\delta} + \hat{\varepsilon}_M^A$, and combining Equations (4A.2) and (4A.3) yields

$$\begin{aligned} p_1^A &= \bar{v}^A + \hat{\delta} + \hat{\varepsilon}_M^A - a(\sigma_v^{2,A} + \rho_v^{A,B}\sigma_v^A\sigma_v^B), \\ p_1^B &= \bar{v}^B + \hat{\delta} + \hat{\varepsilon}_M^B - a(\sigma_v^{2,B} + \rho_v^{A,B}\sigma_v^A\sigma_v^B). \end{aligned} \tag{4A.5}$$

Substituting Equation (4A.5) into the fist order condition, Equation (4A.3) gives

$$\begin{aligned} x_{1,i}^A &= \frac{(\hat{\varepsilon}_i^A - \hat{\varepsilon}_M^A) + (\hat{\varepsilon}_M^B - \hat{\varepsilon}_i^B)\rho_v^{A,B}\dfrac{\sigma_v^A}{\sigma_v^B} + a\sigma_v^{2,A}(1-\rho_v^{2,A,B})}{a\sigma_v^{2,A}(1-\rho_v^{2,A,B})}, \\ x_{1,i}^B &= \frac{(\hat{\varepsilon}_i^B - \hat{\varepsilon}_M^B) + (\hat{\varepsilon}_M^A - \hat{\varepsilon}_i^A)\rho_v^{A,B}\dfrac{\sigma_v^B}{\sigma_v^A} + a\sigma_v^{2,B}(1-\rho_v^{2,A,B})}{a\sigma_v^{2,B}(1-\rho_v^{2,A,B})}. \end{aligned} \tag{4A.6}$$

Investor i at time t = 0 maximizes the following objective function:

$$\max_{x_{0,i}^{A,B}} E_0\{\max_{x_{t,i}^{A,B}} E_1[-\exp\{-a[w_{0,i}+x_{0,i}^A(\tilde{p}_1^A-p_0^A)+x_{1,i}^A(\tilde{v}^A+\tilde{\theta}_i^A-\tilde{p}_1^A) \\ +x_{0,i}^B(\tilde{p}_1^B-p_0^B)+x_{1,i}^B(\tilde{v}^B+\tilde{\theta}_i^B-\tilde{p}_1^B)]\}]\}, \tag{4A.7}$$

or equivalently,

$$\max_{x_{0,i}^{A,B}} E_0[-\exp\{-a[w_{0,i}+x_{0,i}^A(\tilde{p}_1^A-p_0^A)+x_{1,i}^A(\tilde{v}^A+\tilde{\theta}_i^A-\tilde{p}_1^A)-\frac{a}{2}\sigma_v^{2,A}(x_{1,i}^A)^2 \\ +x_{0,i}^B(\tilde{p}_1^B-p_0^B)+x_{1,i}^B(\tilde{v}^B+\tilde{\theta}_i^B-\tilde{p}_1^B)-\frac{a}{2}\sigma_v^{2,B}(x_{1,i}^B)^2]\}]. \tag{4A.8}$$

Substituting the equilibrium $p_1^A, p_1^B, x_{1,i}^A$ and $x_{1,i}^B$ from Equations (4A.5) and (4A.6) into (4A.8) and then maximizing Equation (4A.8) with respect to $x_{0,i}^A$ and $x_{0,i}^B$ with a market clearing constraint, $\sum_{i=1}^M x_{0,i}^A = \sum_{i=1}^M x_{0,i}^B = M$ give

$$\begin{aligned} p_0^A &= \bar{v}^A - a(\sigma_v^{2,A}+\rho_v^{A,B}\sigma_v^A\sigma_v^B+\sigma_\delta^2+\frac{\sigma_\varepsilon^{2,A}}{M}), \\ p_0^B &= \bar{v}^B - a(\sigma_v^{2,B}+\rho_v^{A,B}\sigma_v^A\sigma_v^B+\sigma_\delta^2+\frac{\sigma_\varepsilon^{2,B}}{M}), \\ x_{0,i}^A &= x_{0,i}^B = 1. \end{aligned} \tag{4A.9}$$

Note that optimum holding of bonds at time t = 0 is the same as investors' initial holding. Even though we allow trading to occur at time t = 0, investors just hold their initial endowment because they are still indifferent at this stage.

The trading volumes by investor i, $\Delta x_{1,i}$ for bonds A and B are given by Equation (4.5) and they are normally distributed with zero means and variances of the following forms:

$$\begin{aligned} \sigma_{\Delta x_{1,i}^A}^2 &= \frac{\dfrac{\sigma_\varepsilon^{2,A}(M-1)}{M}+\dfrac{\sigma_\varepsilon^{2,B}(M-1)}{M}\left(\rho_v^{2,A,B}\dfrac{\sigma_v^{2,A}}{\sigma_v^{2,B}}\right)}{\left[a\sigma_v^{2,A}(1-\rho_v^{2,A,B})\right]^2}, \\ \sigma_{\Delta x_{1,i}^B}^2 &= \frac{\dfrac{\sigma_\varepsilon^{2,B}(M-1)}{M}+\dfrac{\sigma_\varepsilon^{2,A}(M-1)}{M}\left(\rho_v^{2,A,B}\dfrac{\sigma_v^{2,B}}{\sigma_v^{2,A}}\right)}{\left[a\sigma_v^{2,B}(1-\rho_v^{2,A,B})\right]^2}. \end{aligned} \tag{4A.10}$$

From Equation (4A.10), the expected trading size of security A by investor i can be obtained by

$$E_0\left(|\,\Delta x_{1,i}^{A}\,|\right) = 2\int_0^{\infty} \frac{z}{\sqrt{2\pi}\sigma_{\Delta x_{1,i}^{A}}} \exp\left[\frac{z^2}{2\sigma^2_{\Delta x_{1,i}^{A}}}\right] dz,$$

where (4A.11)

$$\sigma^2_{\Delta x_{1,i}^{A}} = \frac{\dfrac{\sigma_{\varepsilon}^{2,A}(M-1)}{M} + \dfrac{\sigma_{\varepsilon}^{2,B}(M-1)}{M}\left(\rho_v^{2,A,B}\,\dfrac{\sigma_v^{2,A}}{\sigma_v^{2,B}}\right)}{\left[a\sigma_v^{2,A}(1-\rho_v^{2,A,B})\right]^2}.$$

Solving Equation (4A.11) gives

$$\begin{aligned} E_0\left(|\,\Delta x_{1,i}^{A}\,|\right) &= \sigma_{\Delta x_{1,i}^{A}}\sqrt{\frac{2}{\pi}} \\ &= \frac{1}{a\sigma_v^{2,A}(1-\rho_v^{2,A,B})}\cdot\sqrt{\frac{2}{\pi}\left[\frac{\sigma_{\varepsilon}^{2,A}(M-1)}{M} + \frac{\sigma_{\varepsilon}^{2,B}(M-1)}{M}\left(\rho_v^{2,A,B}\,\frac{\sigma_v^{2,A}}{\sigma_v^{2,B}}\right)\right]}. \end{aligned} \qquad (4A.12)$$

In similar manner, we derive the expected trading size of security *B* by investor *i*.

CHAPTER 5

CONCLUDING REMARKS

In the following three sections, I provide the summary and particular contributions of the thesis and make suggestions for further research.

5.1 Summary of the Thesis

This section summarizes the conclusions of the research. The thesis focuses on liquidity and asset prices. Classical asset pricing usually assumes perfect financial markets without frictions or trading costs. Hence, the diverse features of liquidity are ignored. We have helped to fill this gap by investigating the impacts of liquidity on bond prices in international markets.

In the first research paper, we test the multiple channels of liquidity by extending the liquidity-adjusted capital asset pricing model (LCAPM) of Acharya and Pedersen (2005) to the U.S. dollar sovereign bonds issued by emerging countries during 1995-2008. Our empirical results suggest that liquidity affects cross-sectional differences of bond returns both as a characteristic (liquidity level) and as a risk factor (liquidity risk). As for the economic significance, the effect of liquidity risk or co-movement of the liquidity with the market factors on the expected bond returns can, at times, be greater than that of their own illiquidity cost as measured by the bid/ask spread. In addition, the LCAPM outperforms the standard market-beta CAPM in terms of the empirical fit both in-sample and out-of-sample tests.

As opposed to the unconditional pricing model used in the first research paper and previous literature, the second research paper employs both unconditional and conditional models to study the liquidity impacts on local-currency government bonds in 39 countries (both emerging and developed). In the unconditional setting, liquidity risk (as solely represented in this paper by the return sensitivity to the market liquidity or β^3 in LCAPM) remains the significant pricing factor after controlling for relevant risk factors (i.e., bond market risk, default risk, interest rate term risk and U.S. equity risk factors) as well as bond characteristics (i.e., illiquidity cost, bond duration and bond market value). In the conditional version, we employ a regime switching model and find that liquidity risk is significantly different across good and bad times especially for bonds issued by less-developed nations. The liquidity risk or liquidity commonality is considerably higher in the bad state of the world. However, the price or the premium required by investors for holding this time-varying risk is economically modest.

The two previous papers find liquidity level and shocks to the market-wide liquidity to be priced state variables. Building on these findings, the third research paper studies the dynamics of liquidity transmissions across international bond markets. The key question is what drives liquidity spillovers beyond national boundaries. The mode is developed, which distinguishes between liquidity spillovers or liquidity co-movements caused by idiosyncratic shocks and those caused by systematic shocks. Our empirical tests indicate that the systematic shocks are more important than idiosyncratic shocks in explaining the liquidity commonality (i.e., liquidity risk) across emerging countries in Asia, Europe and Latin America. It follows that investors cannot entirely diversify away liquidity risk by trading with each other. The evidence that liquidity spillover is more systematic than idiosyncratic has important implications for financial market participants. Consistent with the results in the second paper, we also find that our commonality measure in liquidity varies significantly over time and increases strongly during the times of financial distress. As such, a more realistic asset pricing model should acknowledge the existence of liquidity risk and its time-varying dynamics.

5.2 Contributions of the Whole Thesis

Even though we have already described each research paper's contributions in its own chapter, this section summarizes them again. There are five main contributions of this thesis:

1. The thesis is the first to investigate the significance of liquidity both in terms of liquidity <u>level</u> and liquidity <u>risk</u> on international bond prices. Previous studies in asset pricing usually ignore liquidity and those, which consider liquidity, mostly focus their interests on the U.S. equity market and merely on the liquidity level. In addition, our asset pricing tests examine three different channels of liquidity risk and their impacts on bond prices.

2. Typical asset pricing studies center their attention on equity markets. We concentrate on bond markets because, unlike stock returns, the ex ante risk premium for bond returns (or forward-looking yields) can be revealed and this leads to more reliable empirical asset-pricing tests in cross-section.

3. Bonds provide a natural setting in which to explore liquidity effects because they are generally less liquid than equities. For this reason, our test assets cover both domestic (local-currency) and international (U.S. dollar) government bonds issued by both developed and emerging countries. In contrast to previous studies, we use the bid/ask price data to directly measure illiquidity, which has never been compiled before for these bonds

4. This is the first time that the effect of time-varying liquidity risk on international bond prices has been studied. In our conditional pricing model, we also allow both

time-series (using a regime-switching model) and cross-sectional (using Fama-MacBeth (1973) approach) variation in liquidity risks.

5. The question of what causes liquidity contagion, which subsequently generates liquidity risk in international bond markets is investigated in both theoretical and empirical frameworks. We also examine the extent to which systematic and idiosyncratic shocks to liquidity give rise to liquidity spillovers in the international bond markets.

5.3 Suggestions for Future Research

This thesis has investigated the effect of liquidity and liquidity risk on bond prices around the world. Controlling for a number of aggregate risks, liquidity level and global liquidity risk remain important for bond pricing, although liquidity can only explain part of the observed bond yield spreads. Moreover, the impact of liquidity risk is likely to be time varying. Therefore, future research in asset pricing should acknowledge the role of liquidity risk and its dynamics in addition to traditional risk factors such as market risk and default risk. My suggestions for further study are as follows:

(i) Our findings suggest that liquidity risk is time-varying and becomes larger in times when nations experience difficulties. Going forward, research should devote more time to an asset pricing model with time-varying (conditional) liquidity. To achieve a more realistic asset pricing model, the dynamics of liquidity and its significance to asset pricing need to be considered. A more elaborate study of the key determinants of cross-country commonality in liquidity is one of the examples. This is particularly useful for policy makers, who would like to alleviate the potential impact of liquidity risk that can lead to disruptions in their financial markets.

(ii) In the LCAPM and multi-factor model, equilibrium returns compensate investors for expected liquidity cost (liquidity level) and unexpected liquidity co-movement (liquidity risk). The model assumes that the demand for liquidity is inelastic with respect to the magnitude of trading costs and it does not co-vary with other fundamental risks. In other words, we rely on the assumption that it is possible to separate liquidity from other risk factors (e.g., credit risk and market risk). Unexpected change in liquidity can aggravate other risks or can be aggravated by other risks. The interaction of liquidity with other risk factors may explain why the results in previous studies usually underestimate the impact of liquidity (and the impact of other risk factors) on asset prices.

(iii) In addition, this thesis assumes that financial markets are fully integrated. Hence, only global risk factors are important. Despite the evidence that idiosyncratic country factors have almost no explanatory power in explaining yield spreads in the international bond market [108], international investors might not be able to hold locally diversified portfolios at the country level. The local (industry-specific, country-specific and region-specific) risk factors are among the set of omitted variables, which may result in significant pricing errors in many of our pricing regressions. To rectify this, it would be useful to distinguish the impact of local and global risk factors on the bond prices.

(iv) Because of data availability, we employ bid/ask spread as the measure of liquidity. Although it is one of the most direct liquidity measures, one may like to check the robustness of results using other measures. As soon as the data on trading volume or order flow become available for international bond markets[109], we can compute other liquidity measures, such as the Amihud (2002)'s ILLIQ measure of price impact or the Easley, Hvidkjaer and O'Hara

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[108] Many studies (e.g., Kamin and Von Kleist (1999), Eichengreen and Mody (2000) and Arora and Cerisola (2001)) find that risk factors on the U.S. bond markets as proxies for global risk factors are the main determinants of sovereign spreads. Codogna, Favero and Missale (2003), Geyer, Kossmeier and Pichler (2004) and Favero, Pagano and von Thadden (2010) find that yield differentials in EMU countries are driven mainly by a common default risk factor.

[109] For example, the introduction of TRACE and MTS systems make the trading volume data available for U.S. and European bonds.

(2002)'s probability of information-based trading (PIN), which measures the liquidity that is driven by information.

(v) Since the evidence on the term structure of bond market liquidity premia is rare, further investigation of the term structure of liquidity premia might yield useful results. There are a few works, which study the term structures effects of bond liquidity level, for example, Goyenko, Subrahmanyam and Ukov (2008). However, none has studied the term structure of the liquidity risk premium. For portfolio construction, it is important to check which aspect of liquidity (risk or level) is transmitted (or not transmitted) across bond maturity.

(vi) Lastly, it is natural to compare the liquidity risk found in the international bond markets to that in other financial markets, such as the international equity markets. The flight to quality observed in the markets suggests that when stock market faces heavy selling pressure, the government bond market typically encounters heavy buying pressure. There should be liquidity transmission across bond and equity markets.

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